Supplemental Material

Supplemental methods

Sample population

The Faculty of Medicine Imperial College London was established in 1997 and is one of Europe's largest medical institutions.(1, 2) It is organized into the Institute of Clinical Sciences, Kennedy Institute of Rheumatology, Department of Medicine, National Heart and Lung Institute, School of Public Health, and Department of Surgery and Cancer.(1, 2) We used the database from the university intranet to create a list of all academics from the Faculty of Medicine Imperial College that were in employment on the 31st December 2009. For each of the academics included in the study, we extracted the first name, surname, gender, academic rank, and physician status (i.e., whether the academic was a physician or not).(1, 3) We constructed indicator (i.e., binary) variables for gender and physician status. We used the academic rank of lecturer as the reference category against which we controlled for rank-related differences in performance between academics.

For each academic, we recorded the Institute, School or Department with which they were affiliated. Among the six institutional units, we used the Department of Surgery and Cancer as the reference category, against which we controlled for institution-related differences in performance between academics.

For each academic, we used SciVerse Scopus Author Identifier to obtain the publication list.(1, 4) If the search tool identified more than one publication list for an academic's name, then we combined the appropriate publication lists. For each academic, we examined the publication list and excluded any publications that were not attributable to the individual academic. All publication lists were divided into three time periods (January 1st 2001 to December 31st 2003; January 1st 2004 to December 31st 2006; and January 1st 2007 to December 31st 2009). This enabled us to carry out a longitudinal analysis of the role that collaborative and authorship practices had in sustaining research performance. For each academic and time period, we calculated the total number of citations received by all articles the academic published in that time period.(1, 5-10) In this way, the effects of collaborative and authorship patterns on the academic's research performance could be unambiguously assessed.

Creating the co-authorship network

For each time period, we combined the publication lists of all academics into a single list, which was stored as a comma-separated value (.csv) file. Each file was loaded into Network Workbench Software, which is a software for the analysis, modeling and visualization of large-scale networks.(11) The software filtered out the duplicate publications resulting from the combination of the publication lists of academics that co-authored publications. The co-authorship network was then extracted from the remaining publications and was stored as a network (.net) file. The nodes of the network were the authors, and links were established between any two nodes when the corresponding authors had co-authored one or more scientific publications.(12) The network so constructed is therefore undirected and unweighted. The largest connected component(13) of the network shown in figure 2 in the main text was produced through the software Visone.(14)

We used the Network Workbench Software to calculate six network measures: (i) degree centrality, (ii) eigenvector centrality, (iii) betweenness centrality, (iv) closeness centrality, (v) local clustering coefficient and (vi) constraint. Each of these measures will, in turn, be defined and discussed in what follows.(13, 15-18)

Measuring authors' network-based centrality

The normalized degree centrality of a node is the number of links incident upon the node, divided by its maximum possible value (i.e., the number of nodes in the network minus one) (figure S1A).(13, 15) Formally, for an undirected network of *n* nodes and no self-edges, the degree centrality of node *i* can be expressed in terms of the adjacency matrix *A* as:

$$C_D(i) = k_i = \sum_j A_{ij},$$

where

$$A_{ij} = \begin{cases} 1 \text{ if there is a link between nodes } i \text{ and } j \ (i \neq j); \\ 0 \text{ otherewise.} \end{cases}$$

To obtain the normalized degree centrality of node *i*, $C_D^{'}(i)$, we simply divide $C_D(i)$ by its maximum value, i.e., $n-1$:

$$C_D^{'}(i) = \frac{C_D(i)}{n-1}.$$

A large body of literature has suggested that highly connected nodes have a greater chance of receiving information and having more influence or prestige than poorly connected ones.(19, 20) We tested the hypothesis that academics with more collaborators (i.e., with a higher normalized degree centrality) were more likely to be exposed to a larger amount of information and opportunities and could therefore achieve a better performance than academics with fewer collaborators (i.e., with a low normalized degree centrality).

Degree centrality is a local measure of centrality, and as such does not depend on the global structure of the network. Although a node may be highly connected, it may not be suitably located so as to reach others and receive or send information quickly within the network. For this reason, we also tested the effects of global measures of centrality on academics' performance.

Eigenvector centrality measures the importance of a node in a network as a function of the connections the node has to other nodes that are themselves important (figure S1A).(21) Instead of awarding a node only one score for each of its neighbors, eigenvector centrality awards the node a score that is proportional to the sum of the scores of its neighbors. Formally, we have:

$$C_E(i) = \kappa_1^{-1} \sum_j A_{ij} C_E(j),$$

where κ_1 is the largest eigenvalue of the adjacency matrix A and C_E is the associated eigenvector. The measure is therefore premised on the idea that the centrality of a node is high to the extent that the node's neighborhood includes many nodes or nodes that also have a high centrality, or both. We tested the hypothesis that academics with a higher value of eigenvector centrality could achieve a better performance than academics with a lower value.

Betweenness centrality measures the extent to which a node lies on the shortest paths between other nodes in the network (figure S1A).(15, 18) Betweenness centrality captures the ability of a node to control interactions and information flows between pairs of other nodes in the network, and thus to act as the gatekeeper or broker between others. Formally, we have:

$$C_B(i) = \sum_{j,l} \frac{g_{j,l}(i)}{g_{j,l}},$$

where $g_{j,l}$ is the number of geodesics (i.e., shortest paths) linking nodes j and l, for i distinct from j and l; $g_{j,l}(i)$ is the number of such geodesics that contain node i; and $\frac{g_{j,l}(i)}{g_{j,l}} = 0$ if both $g_{j,l}(i)$ and $g_{j,l}$ are zero. Nodes with higher betweenness centrality are expected to have a higher status, power or influence on others than nodes with lower betweenness. We therefore tested the hypothesis that academics with higher betweenness could achieve better research performance than academics with lower betweenness.

Finally, a node's closeness centrality is defined as the inverse of the sum of the shortest distances separating the node from all other nodes, and thus measures how close the node is to all other nodes in the network (figure S1A).(12, 15) Formally, we have:

$$C_C(i) = \left[\sum_j d_{i,j} \right]^{-1},$$

where $d_{i,j}$ is the length of the geodesic path from node *i* to node *j*, i.e., the number of links along the path. Nodes with higher closeness centrality are expected to obtain information more promptly, and exert more influence on others, than nodes with lower closeness. We therefore tested the hypothesis that academics with higher closeness could obtain a higher performance than academics with lower closeness.

Measuring authors' social capital: Closed versus open network structures

We investigated the role of social capital in facilitating academics' performance, by testing the effects that closed and open network structures had on academics' citation counts. We relied on two network measures: the local clustering coefficient(16) and network constraint.(17)

Local clustering coefficient is defined as the ratio between the number of links connecting pairs of a node's neighbors and the total number of pairs of the node's neighbors (figure S1B).(16) Formally, we have:

$$Clust(i) = \begin{cases} \dfrac{K[N_i]}{k_i(k_i - 1)/2} & \text{for } k_i \geq 2 \\ 0 & \text{for } k_i = 0,1 \end{cases},$$

where $K[N_i]$ is the number of links connecting pairs of the neighbors N_i of node *i*, and k_i is the degree (i.e., the number of neighbors) of node *i*. The clustering coefficient has traditionally been used to operationalize conceptions of social capital predicated on the mechanism of social cohesion and network closure.(22) From this perspective, clustering captures the extent to which a node can derive benefits from being socially embedded within cohesive social structures, rich in third-party relationships. Among these closure-based sources of social capital are normative control, deviance avoidance, the enhancement of one's sense of belonging and trust, the creation of a common culture, and the facilitation of cooperation and of the exchange of fine-grained, complex, tacit and proprietary information.(23) We tested the hypothesis that academics whose local network was more socially cohesive (i.e., with a higher clustering coefficient) could obtain a better performance than academics in a less cohesive network (i.e., with lower clustering).

Innovative biomedical research often necessitates strong support from colleagues who are experts in similar areas, but also requires access to the diverse sources of knowledge in other specialties. While closed networks facilitate social support and knowledge flows, individuals can also benefit from participating in open structures that are rich in cleavages and opportunities of brokerage. This is the idea underpinning an alternative conception of social capital: by gaining exposure to a greater variance and novelty of information, individuals embedded in brokered structures will be creative and successful in their endeavors.(17, 23-

25) Structural holes are opportunities for individuals to broker between otherwise disconnected individuals. Individuals closely linked with one another are likely to possess similar ideas: the more an individual's contacts are connected with each other, the less likely they are to take the individual closer to valuable sources of knowledge and resources that the individual is not already able to access. Highly cohesive networks may thus create isolation and resistance to information and knowledge flowing from outside the network. By contrast, when an individual's contacts are disconnected from each other, the presence of structural holes may provide the individual with opportunities for gaining access to new and non-redundant social circles in which other individuals are likely to have different ideas and resources.

Network constraint measures the extent to which a node is connected to other nodes that are already connected with each other (figure S1C). Formally, the constraint of node *i* has been defined by Burt(17) as:

$$Constr(i)=\sum_{j}\left(p_{i,j}+\sum_{q}p_{i,q}p_{q,j}\right)^{2},\; q\neq i,j,$$

where $p_{i,j}$ is the entry of the transition matrix *P* and measures the proportion of node *i*'s network time and energy invested in the relationship with node node *j*, and (for undirected networks) is defined as

$$p_{i,j}=\frac{w_{i,j}}{\sum_{m}w_{i,m}},\; i\neq j,$$

where $w_{i,j}$ is the weight of the link connected nodes *i* and *j* (25). Constraint thus captures the lack of structural holes in a network. A low value of network constraint means that a node can broker between otherwise disconnected others, and can therefore benefit from discontinuities in the social structure. On the other hand, a large value of network constraint implies paucity of connections to non-redundant others, and is therefore associated with network closure. We tested the hypothesis that academics with a lower value of network constraint could achieve better performance than academics with a higher value.

Extracting authors' positions in bylines

The position of an author in the list of co-authors of a publication is often used to indicate the relative importance of the contribution of the author to the scientific work.(26-33) Our data retained this important information on authorship credit, which we used to assess the association between an author's position and research performance. For each multi-authored publication, and distinguishing between publications in which co-authors were listed in alphabetical and non-alphabetical order, we extracted the four most important positions, classified as follows:

- The first-listed author on any multi-authored publication was always recorded as "first author".

- The last-listed author was recorded as “last author” provided the publication had two or more co-authors.
- The second-listed author was recorded as “second author” provided the publication had at least three co-authors.
- The penultimate author was recorded as “penultimate author” provided there were at least four co-authors on the publication.
- Any remaining position was recorded as “other”.

For each academic and for each time period, we extracted the number of multi-authored publications in which co-authors were listed alphabetically and non-alphabetically. For each of these two groups of publications, we recorded the number of publications in which the academic appeared as listed in each of the above five positions. In total, for each academic and time period, we therefore constructed ten position-related variables, and then tested the effect of these variables on the academic’s performance.(34-36)

Statistical analysis

Table S1 shows the zero-order correlations between variables. Table S2 reports the within and between variations of all variables. Table S3 shows the transition probabilities from one period to the next, and table S4 the first-order autocorrelations of citations.

Models 1 through to 3 in table 3 include various centrality measures. These measures could not be included simultaneously in one single model because the high degree of correlation between them would have created problems of multi-collinearity.

As shown in tables 2 and S2, the dependent variable (citations) is considerably overdispersed, since the sample variance of 655.47 is about 1.58 as large as the sample mean of 414.42. The default standard errors for both cross-section and panel estimators would therefore understate the true standard errors.

Both the dependent variable and the regressors can potentially vary over time (within variation) and individuals (between variation). As indicated by table S2, time-invariant regressors (e.g., gender) have zero within variation. For most of the other regressors as well as the dependent variable, there is more variation across individuals than over time. The coefficients of regressors with relatively little within variation estimated with a fixed-effects model would be imprecise (and not identified when there is no within variation at all). Within estimation may therefore lead to considerable efficiency loss.

To examine the variation of the dependent variable in more detail, we calculated the transition probabilities from one period to the next, after aggregating citations into appropriate categories. Table S3 shows that there was considerable persistence in performance from one period to another one. Over 65% of the authors with no citations in one time period also did not receive any citation in the subsequent period, while over 38% of the authors with more than 1,000 citations in one period received more than 1,000 citations in the subsequent period. Table S4 shows the first-order autocorrelations at all lags. Clearly, citations were correlated over time, and autocorrelations varied little with lag length.

Modeling strategy

Table S5 shows the estimated coefficients for institutional affiliation that were not reported in the four random-effects negative binomial panel models of table 1. Findings indicate statistically significant differences in performance between academic departments (e.g., between the School of Public Health and the Department of Surgery and Cancer).

Tables S6a and S6b summarize estimated coefficients and standard errors for different estimators. Model 5 refers to the pooled quasi-maximum likelihood Poisson estimator with cluster-robust standard errors that control for both overdispersion and serial correlation over time for a given individual. Note that the default standard errors (not reported here) that impose the restriction of mean-variance equality are smaller. Correcting for overdispersion using the sandwich variance matrix estimate would increase the standard errors estimates (not reported here). This points to the importance of controlling for overdispersion (see below). Moreover, controlling for serial correlation over time for a given individual produces even larger cluster-robust standard error estimates (Model 5). Similarly, Model 6 refers to the pooled quasi-maximum likelihood negative binomial estimator with cluster-robust standard errors that control for both overdispersion and serial correlation.

Efficiency gains can be obtained if estimation is based on a specified model for the dependence over time for a given individual. To this end, we also estimated generalized estimating equations (GEE) or population-averaged models with different correlation structures. Model 7 refers to the GEE Poisson model with unstructured error correlation, i.e., with no restriction on the correlation of errors over time aside from their equality across individuals. Model 8 refers to the GEE negative binomial model with unstructured error correlation. Model 9 is the GEE Poisson estimator with equicorrelated errors. Model 10 is the GEE negative binomial estimator with equicorrelated errors. Model 11 is the Poisson maximum likelihood panel estimator with gamma-distribued random effects and cluster-robust bootstrapped standard errors (with 100 replications). Model 12 refers to the conditional maximum likelihood fixed-effects negative binomial panel estimator with both individual- and time-specific effects and cluster-robust boostrapped standard errors (with 100 replications). The computation of all models was implemented using Stata 64/MP 10.1.

The coefficient estimates of the pooled models are quite similar to those from the corresponding population-averaged models. Compared with the parameter estimates from the population-averaged models, the random-effects estimated coefficients differ roughly by 20-30%. The random-effects Poisson and negative binomial estimates and their standard errors are similar. Notice that the negative binomial fixed-effects estimator (Model 12) is unusual in that, unlike other fixed-effects linear estimators, it provides estimates for time-invariant regressors in addition to time-varying ones.[(37)] However, notice that fixed-effects estimates of most time-invariant regressors are not statistically significant.

For all panel models, likelihood-ratio (LR) tests of model specification indicates that they are more appropriate than the corresponding pooled models, i.e., $p\left(\chi^2(1) > LR\right) < 0.001$.

Specification tests

1. Testing for overdispersion

There are several methods of testing for overdisperion. A regression-based overdispersion test statistic can be computed by estimating the random-effects panel Poisson model, running the auxiliary OLS regression (without constant) of the generated dependent variable, $\left\{\left(y - \hat{\mu}\right)^2 - y\right\} / \hat{\mu}$, on $\hat{\mu}$, and conducting a *t* test of whether the coefficient of $\hat{\mu}$ is zero, where $\mu = \exp\left(x'\beta\right)$ (38). We obtained a *t* value of 31.25 (p<0.001), which is an indication of significant overdispersion.

Because the log-likelihood functions of both the panel Poisson model and panel negative binomial model can be easily obtained, the LR test statistic can also be used to test for overdispersion. We conducted a LR test that compares the estimates from the random-effects negative binomial panel model with those from the random-effects panel Poisson model, where standard errors were estaimated through 100 bootstrap replications. The null hypothesis is $H_0 : \alpha = 0$, where the scalar parameter α specifies the conditional variance $Var\left(y_i \middle| x_i\right) = \mu_i + \alpha\mu_i^2$. Thus, the null hypothesis is that there is no overdispersion, and implies that the negative binomial model reduces the Poisson one. The LR test statistic is: LR = -2(LLF_r – LLF_u), where LLF_r is the maximised value of the restricted log-likelihood function of the Poisson model, and LLF_u is the maximised value of the unrestricted log-likelihood function of the negative binomial model. Asymptotically LR follows the χ^2 distribution. Since there is only one constraint, the degree of freedom is one. We obtained: LR = -2(-7,0132.897 + 8,460.0336) = 123,345.7268. Thus, $p\left(\chi^2(1) > 123{,}345.7268\right) < 0.001$, which provides further support in favor of the hypothesis of overdispersion. That is, because α is significantly different from zero, the LR test suggests that the Poisson distribution is not appropriate.

2. Unobserved heterogeneity: Fixed versus random effects

The analysis of panel data is often affected by the problem of unobserved time-invariant effects known as “unobserved heterogeneity”.(39) This is particularly relevant to our study since a prior history of successful publications may affect the future likelihood of further successful publications. We dealt with this possibility of “state dependence” (i.e., the likelihood of an event being a function of the state of the unit) by including in our models the number of past publications among the covariates. However, we did not include a lagged dependent variable.

In addition to state dependence, there is another potential problem that, if not properly accounted for, could lead to spurious results. Authors may differ in their ability to produce articles of high impact because of unobserved factors. These factors could arise from permanent differences among the authors, such as intellecutal skills, not captured by the independent variables. If this noise were systematic for the same authors over time, it could lead to a serial correlation among the error terms for those authors, and would produce consistent but inefficient estimated coefficients. Moreover, past productivity may seem to promote future scientific performance simply because it is a proxy for time-invariant unobservable factors that facilitate or hinder the publication of articles of high impact. Failure to address this "spurious state dependence"(39) can also induce biases in the estimates.

The problem of unobserved heterogeneity is directly related to model specification. If the model does not suffer from a problem of omitted variable, no such problem would occur. However, most statistical models are not fully specified. One possible solution would be to refine the sample. In our study we included all faculty members in the set of scientists at risk of publishing an article. However, it may be the case that some of these academics were in fact not at risk of publishing high-impact articles or even publishing any article in some or all observation periods, while others had a higher propensity to publish. This may suggest the possibility of misspecification of the sample population, and may justify attempts to clean up the risk set by eliminating observations unlikely to experience the event. However, differences in propensity to publish high-impact articles were likley to originate from unobservable individual effects. Simply filtering out a subset of individuals from the sample would therefore have been inappropriate and would have biased the sample itself.

Two models traditionally used to address problems of unobserved heterogeneity are the fixed-effects and random-effects models.(38) Fixed-effects models treat the unobserved individual-specific effect as invariant over time and compute it for each panel (author). This method would thus estimate a constant term for each distinct author. By contrast, random-effects models treat the indicidual-specific effects as randomly drawn from some underlying probability distribution. There is a vast body of literature concerned with the strenghts and shortcomings of fixed-effects models versus random-effects ones in the linear case (40), and the same comparative assessement extends to the case of non-linear models.(37)

To address concerns of heterogeneity, in this study we employed a random-effects panel negative binomial model, which introduces two additional parameters to account for both overdispersion and within correlation. Our choice of the random-effects estimator was motivated as follows. First, unlike random-effects models, fixed-effects ones would produce biased estimates when panels extend over relatively short periods.(39, 40) Because all authors in our sample were present for only three periods of time, the random-effects model was clearly the favored estimator. Second, fixed-effects models (but with the exception of the negative binomial estimator(37)) cannot include time-independent regressors because they would be absorbed into the individual-specific effects and would not be identified. In our case, this limitation would have implied the exclusion of a number of covariates, such as gender, physician status and academic rank, and as a result the analysis would have been severely limited. For instance, we could not have estimated the interaction effects between academic rank and position in byline. Third, we used a random-effects panel regression model so that we could obtain an unconditional inference. Consequently, the results are not restricted to the particular individuals sampled, but can be generalized to the population of biomedical scientists from which the sample was drawn. Finally, to test whether individual-specific unobservables are uncorrelated with individual-specific observables, we conducted a Hausman test to compare the estimated coefficients of the two-way fixed-effects negative binomial estimator with both individual- and time-specific effects with the estimated coefficients of the random-effects negative binomial estimator with time dummies. The null hypothesis is that there is no statistically significant difference between the estimates of the models, and thus that there is no need for fixed-effects estimation. The test produced: $H = 38.40 < \chi^2_{.05}(38) \approx 55.758$ or, alternatively, $p\left(\chi^2(38) > 55.758\right) = 0.4514 > 0.05$. Thus, the test does not reject the null hypothesis that the individual-specific effects are uncorrelated with the regressors and that the random-effects estimator produces consistent (and efficient) estimates.

We also addressed concerns of heterogeneity by replicating the analysis using two groups of increasingly restrictive definitions of the risk set. To restrict the analysis to authors of comparable scientific productivity, the first three sets included all authors who, across all three periods of time, had a history of, respectively, at least one publication (n=479), five publications (n=449), and 10 publications (n=369). To restrict the analysis only to authors with comparable propensity to enagage in collaborative teams, we produced three additional risk sets: one including only authors who published at least five multiple-authored articles (n=450); another including only authors who never published any solo-authored article (n=397); and another including only authors who published at least five multiple-authored publication and never published any solo-authored article (n=326). We finally created two more risk sets: one including only authors who, across all periods of time, had a history of at least one publication and published at least five multiple-authored articles (n=424); the other including only authors with a history of at least one publication and who never published any solo-authored article (n=383). The results obtained with different subsets were qualitatively similar, and we reported only those based on the complete sample.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1	1.00																														
2	0.56	1.00																													
3	0.12	0.12	1.00																												
4	0.05	0.08	0.15	1.00																											
5	-0.02	-0.03	0.03	0.01	1.00																										
6	0.01	0.01	-0.02	-0.03	-0.04	1.00																									
7	-0.09	-0.01	-0.01	0.07	-0.14	-0.18	1.00																								
8	0.09	0.09	-0.01	-0.02	-0.08	-0.11	-0.41	1.00																							
9	0.11	-0.03	-0.06	-0.09	-0.06	-0.08	-0.29	-0.17	1.00																						
10	-0.18	-0.17	-0.08	0.21	0.01	0.02	0.01	-0.05	0.02	1.00																					
11	-0.07	-0.06	-0.03	-0.09	0.01	-0.06	0.07	0.00	0.02	-0.22	1.00																				
12	0.39	0.35	0.18	0·08	-0.07	-0.02	-0.02	0.10	0.01	-0.49	-0.32	1.00																			
13	0.14	0.01	0.00	-0·02	0.04	-0.03	-0.01	-0.02	0.08	-0.03	-0.03	0.04	1.00																		
14	-0.18	-0.15	-0.06	-0·14	0.03	-0.03	0.04	-0.07	-0.06	0.02	-0.03	-0.22	0.36	1.00																	
15	0.55	0.40	0.08	0·06	0.00	-0.02	-0.09	0.07	0.10	-0.11	-0.02	0.26	0.23	-0.11	1.00																
16	0.48	0.28	0.11	0·09	-0.02	0.01	-0.08	0.05	0.07	-0.13	-0.03	0.29	0.15	-0.14	0.84	1.00															
17	0.39	0.38	0.07	0·05	0.01	0.00	-0.03	0.07	0.00	-0.06	0.02	0.19	0.03	-0.04	0.49	0.27	1.00														
18	0.23	0.21	0.05	0·02	0.00	0.01	-0.04	0.08	-0.01	-0.03	0.02	0.05	0.02	-0.03	0.73	0.52	0.37	1.00													
19	-0.30	-0.24	-0.10	-0.06	0.01	0.00	0.04	-0.03	-0.06	0.12	-0.02	-0.36	-0.02	0.29	-0.29	-0.36	-0.13	-0.05	1.00												
20	-0·14	-0.11	-0.09	-0.04	-0.02	0.00	0.00	-0.03	0.05	0.10	-0.02	-0.16	-0.13	0.04	-0.17	-0.16	-0.16	-0.08	0.30	1.00											
21	0.27	0.37	0.09	0.14	-0.04	0.00	0.01	0.12	-0.02	-0.10	-0.04	0.24	-0.05	-0.16	0.12	0.15	0.07	0.01	-0.15	-0.07	1.00										
22	0.11	0.04	0.00	0.08	-0.03	-0.02	-0.08	0.02	0.03	0.07	0.06	-0.11	-0.08	-0.18	0.06	0.07	0.08	0.01	-0.10	-0.01	0.18	1.00									
23	0.56	0.49	0.14	0.11	-0.03	-0.02	-0.08	0.10	0.00	-0.23	-0.06	0.47	-0.03	-0.25	0.32	0.43	0.14	0.07	-0.34	-0.13	0.33	0.04	1.00								
24	0.36	0.23	0.05	0.04	-0.01	-0.04	-0.11	0.03	0.08	-0.09	0.03	0.15	0.00	-0.20	0.25	0.29	0.12	0.09	-0.24	-0.09	0.14	0.35	0.38	1.00							
25	0.46	0.42	0.14	0.06	-0.01	-0.01	-0.08	0.07	0.03	-0.20	-0.05	0.38	0.06	-0.15	0.31	0.44	0.10	0.07	-0.29	-0.11	0.26	0.03	0.68	0.38	1.00						
26	0.50	0.25	0.07	0.06	0.03	-0.01	-0.10	0.04	0.16	-0.14	-0.02	0.28	0.53	-0.13	0.47	0.44	0.10	0.08	-0.28	-0.14	0.15	0.13	0.39	0.41	0.47	1.00					
27	0.14	0.12	0.04	0.06	-0.01	0.01	-0.07	0.05	0.04	-0.01	0.02	0.05	-0.14	-0.22	0.07	0.10	0.05	0.01	-0.12	-0.04	0.20	0.12	0.21	0.18	0.15	0.06	1.00				
28	0.21	0.21	0.08	0.09	-0.06	0.08	-0.02	0.08	-0.05	-0.11	-0.08	0.27	-0.11	-0.23	0.12	0.19	0.04	0.00	-0.19	-0.07	0.27	0.18	0.34	0.15	0.27	0.13	-0.07	1.00			
29	0.10	0.08	0.04	-0.03	0.00	-0.02	-0.05	0.01	0.09	-0.05	-0.02	0.11	-0.07	-0.09	0.06	0.10	0.03	0.01	-0.12	-0.05	0.06	0.08	0.15	0.17	0.13	0.07	0.06	0.06	1.00		
30	0.09	0.04	0.07	0.06	-0.03	-0.03	-0.02	0.06	0.00	-0.05	-0.02	0.09	-0.02	-0.05	0.08	0.11	0.05	0.09	-0.07	-0.03	0.04	0.11	0.13	0.09	0.09	0.06	0.01	0.11	0.12	1.00	
31	0.07	0.10	0.07	0.04	0.01	-0.02	-0.03	0.08	-0.04	-0.04	-0.01	0.05	0.00	-0.01	0.06	0.04	0.03	0.06	-0.03	-0.02	0.04	-0.01	0.08	0.01	0.07	0.05	0.01	0.09	0.00	0.04	1.00

Appendix Table S1 Zero-order correlations between variables

		Standard deviation		
		Overall	Between	Within
Dependent variable	Number of citations	655.472	543.952	366.264
Control variables	Number of past publications	58.252	39.503	42.836
	Gender	0.456	0.457	0.000
	Physician status	0.500	0.500	0.000
	Senior lecturer	0.437	0.437	0.021
	Reader	0.332	0.332	0.000
	Professor	0.492	0.492	0.000
	Institute of Clinical Sciences	0.161	0.161	0.000
	Kennedy Institute of Rheumatology	0.209	0.209	0.000
	Department of Medicine	0.492	0.492	0.021
	National Heart Lung Institute	0.398	0.397	0.021
	School of Public Health	0.311	0.311	0.000
Solo versus multiple authorship	Solo-authored articles	2.986	2.701	1.277
	Median number of co-authors per publication	3.313	2.568	2.078
	(Median number of co-authors per publication)^2	62.842	45.325	42.707
	Minimum number of co-authors per publication	1.620	1.216	1.087
Network-based measures of centrality	Degree	0.021	0.015	0.014
Network-based measures of social capital	Constraint	0.328	0.202	0.258
Author's position in publication Position in non-alphabetized bylines	First	2.540	1.972	1.603
	Last	6.900	6.321	2.775
	Second	2.418	1.907	1.488
	Penultimate	4.327	3.659	2.312
	Other	7.089	6.156	3.523
Author's position in publication Position in alphabetized bylines	First	0.928	0.702	0.608
	Last	1.398	1.189	0.736
	Second	0.429	0.291	0·316
	Penultimate	0.168	0.112	0.126
	Other	0.133	0.081	0.105
Interactions: academic rank and position	Senior lecturer X non-alphabetical last position	1.810	1.559	0.920
	Reader X non-alphabetical last position	1.566	1.088	1.127
	Professor X non-alphabetical last position	5.963	5.487	2.341
	Senior lecturer X alphabetical first position	0.437	0.326	0.292
	Reader X alphabetical first position	0.331	0.215	0.252
	Professor X alphabetical first position	0.635	0.498	0.394
Interactions: academic rank, position, and brokerage	Senior lecturer X non-alphabetical last position X constraint	1.049	0.630	0.839
	Reader X non-alphabetical last position X constraint	0.213	0.133	0.165
	Professor X non-alphabetical last position X constraint	0.687	0.587	0.322

Appendix Table S2 Within and between variation of the dependent variable and the regressors

Citations	0-49	50-99	100-199	200-299	300-399	400-499	500-799	800-999	1000-	Total
0-49	65.03	11.19	11.19	4.90	1.40	0.70	4.90	0.70	0.00	100.00
50-99	45.78	22.89	19.28	6.02	1.20	2.41	1.20	1.20	0.00	100.00
100-199	27.78	27.78	27.22	6.67	6.11	1.11	3.33	0.00	0.00	100.00
200-299	17.78	20.74	34.81	9.63	5.19	6.67	2.22	2.22	0.74	100.00
300-399	12.94	20.00	30.59	15.29	12.94	2.35	4.71	1.18	0.00	100.00
400-499	7.69	16.92	26.15	18.46	13.85	4.62	6.15	4.62	1.54	100.00
500-799	3.88	9.30	18.60	24.81	12.40	10.08	13.18	1.55	6.20	100.00
800-999	2.33	6.98	13.95	25.58	2.33	11.63	20.93	4.65	11.63	100.00
1000-	1.34	0.00	4.03	7.38	6.71	12.75	22.15	7.38	38.26	100.00
Total	22.63	15.42	20.45	11.46	6.72	5.53	8.30	2.37	7.11	100.00

Appendix Table S3 Transition probabilities

Time period	1	2	3
1	1.0000		
2	0.7905	1.0000	
3	0.6889	0.6870	1.0000

Appendix Table S4 First-order autocorrelation of citations from one period to another

	Model 1		Model 2		Model 3		Model 4	
Control variables	EC	SE	EC	SE	EC	SE	EC	SE
Institute of Clinical Sciences	1.266	0.155	1.284	0.167	1.231	0.163	1.264	0.165
Kennedy Institute of Rheumatology	1.158	0.142	1.125	0.133	1.222	0.163	1.267*	0.127
Department of Medicine	1.025	0.081	1.025	0.058	1.074	0.077	1.044	0.062
National Heart Lung Institute	1.174	0.122	1.189*	0.102	1.145	0.108	1.174	0.101
School of Public Health	1.273*	0.122	1.302**	0.129	1.292*	0.141	0.232*	0.123
Number of observations	1,285		1,285		1,320		1,285	
Number of groups	490		490		494		490	
Wald chi square	1,598.99		1,232.76		1,666.49		1,178.38	
Prob > ChiSq	0.000		0.000		0.000		0.000	
Log pseudolikelihood	-8,495.893		-8,513.934		-8,517.552		-8,460.034	

EC = estimated coefficient; SE = bootstrap standard error
* p < 0.05, ** p < 0.01, *** p<0.001

Appendix Table S5 Results of negative binomial random-effects panel regressions not reported in table 3. For ease of interpretation, and like table 3, the table displays incidence rate ratios. The reference category for the institutional unit is the Department of Surgery and Cancer.

	Model 5		Model 6		Model 7		Model 8	
	EC	SE	EC	SE	EC	SE	EC	SE
Control variables								
Number of past publications	0.002**	0.000	0.003**	0.001	0.002**	0.000	0.002**	0.001
Gender	0.169*	0.076	0.145*	0.065	0.172*	0.084	0.142*	0.063
Physician status	-0.132	0.073	-0.220**	0.062	-0.073	0.073	-0.203**	0.061
Senior lecturer	0.461*	0.200	0.259	0.236	0.464	0.356	0.304	0.240
Reader	0.516**	0.201	0.452	0.236	0.556	0.351	0.490*	0.249
Professor	1.026**	0.190	0.755**	0.230	1.080**	0.345	0.794**	0.234
Solo versus multiple authorship								
Solo-authored articles	0.006	0.008	0.008	0.014	0.013	0.008	0.012	0.010
Median number of co-authors per publication	0.029	0.015	0.049**	0.015	0.024	0.019	0.049**	0.013
(Median number of co-authors per publication)^2	-0.003**	0.001	-0.003**	0.001	-0.002**	0.001	-0.002**	0.001
Minimum number of co-authors per publication	-0.079**	0.027	-0.072**	0.019	-0.039	0.034	-0.070**	0.024
Network-based measure of centrality								
Degree	6.810**	1.251	14.039**	3.329	5.247**	1.103	9.259**	1.392
Network-based measure of social capital								
Constraint	-1.032**	0.266	-0.797**	0.269	-0.967**	0.344	-0.873**	0.251
Author's position in publication								
Position in non-alphabetized byline:								
First	0.034**	0.011	0.065**	0.016	0.024*	0.012	0.061**	0.013
Last	-0.120*	0.047	-0.104	0.055	-0.128	0.090	-0.104	0.060
Second	0.030*	0.014	0.043**	0.014	0.033**	0.013	0.037	0.014
Penultimate	-0.008	0.009	0.003	0.012	-0.004	0.009	0.003	0.010
Other	0.028**	0.007	0.032**	0.010	0.029**	0.010	0.040**	0.007
Position in alphabetized byline:								
First	-0.002	0.036	0.003	0.054	0.078*	0.033	0.039	0.051
Last	0.012	0.020	0.030	0.024	0.016	0.020	0.031	0.023
Second	0.017	0.040	0.084	0.056	0.067	0.045	0.113*	0.049
Penultimate	0.020	0.135	-0.103	0.129	-0.186	0.159	-0.219	0.172
Other	0.047	0.147	0.039	0.174	0.041	0.135	0.036	0.163
Interactions: academic rank and position								
Senior lecturer X non-alphabetical last position	0.102*	0.050	0.091	0.058	0.124	0.092	0.106	0.061
Reader X non-alphabetical last position	0.066	0.052	0.085	0.066	0.103	0.092	0.097	0.063
Professor X non-alphabetical last position	0.160**	0.047	0.157**	0.055	0.166	0.090	0.155**	0.060
Senior lecturer X alphabetical first position	0.186	0.105	0.231*	0.114	0.182	0.135	0.195	0.123
Reader X alphabetical first position	-0.045	0.086	-0.016	0.091	-0.074	0.071	-0.033	0.081
Professor X alphabetical first position	0.050	0.049	0.008	0.064	-0.010	0.047	-0.008	0.061
Interactions: academic rank, position, and brokerage								
Senior lecturer X non-alphabetical last position X	0.005	0.214	-0.202*	0.081	-0.153	0.232	-0.230**	0.076
Reader X non-alphabetical last position X constraint	0.084	0.151	0.347	0.333	0.230	0.130	0.400**	0.134
Professor X non-alphabetical last position X constraint	0.201**	0.049	0.333**	0.082	0.220**	0.061	0.300**	0.055
Number of observations	1285		1285		1285		1285	
Number of groups	490		490		490		490	
Wald chi square	1851.38		850.880		1079.680		1283.600	
Prob > ChiSq	0.000		0.000		0.000		0.000	
Log pseudolikelihood	-157048.170		-8484.234					
Pseudo R2	0.606							

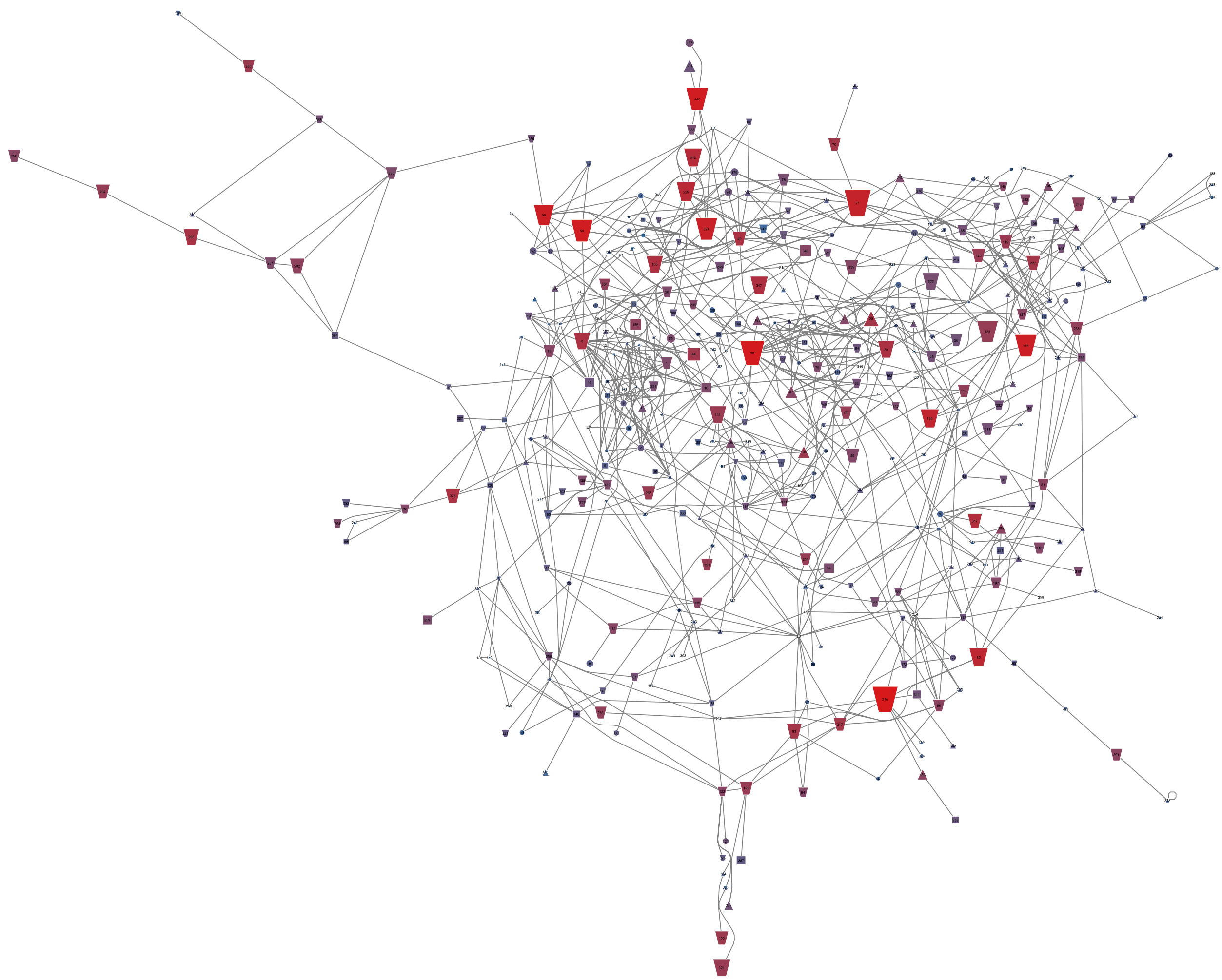
EC = estimated coefficient; SE = standard error
* $p < 0.05$, ** $p < 0.01$

Appendix Table S6a Estimated parameters from various regression models. Model 5 is the pooled quasi-maximum likelihood Poisson estimator with cluster-robust standard errors. Model 6 is the pooled quasi-maximum likelihood negative binomial estimator with cluster-robust standard errors. Model 7 is the GEE Poisson model with unstructured error correlation. Model 8 is the GEE negative binomial model with unstructured error correlation. Unlike tables 3 and S5, this table reports Poisson or negative binomial (unexponentiated) estimated coefficients.

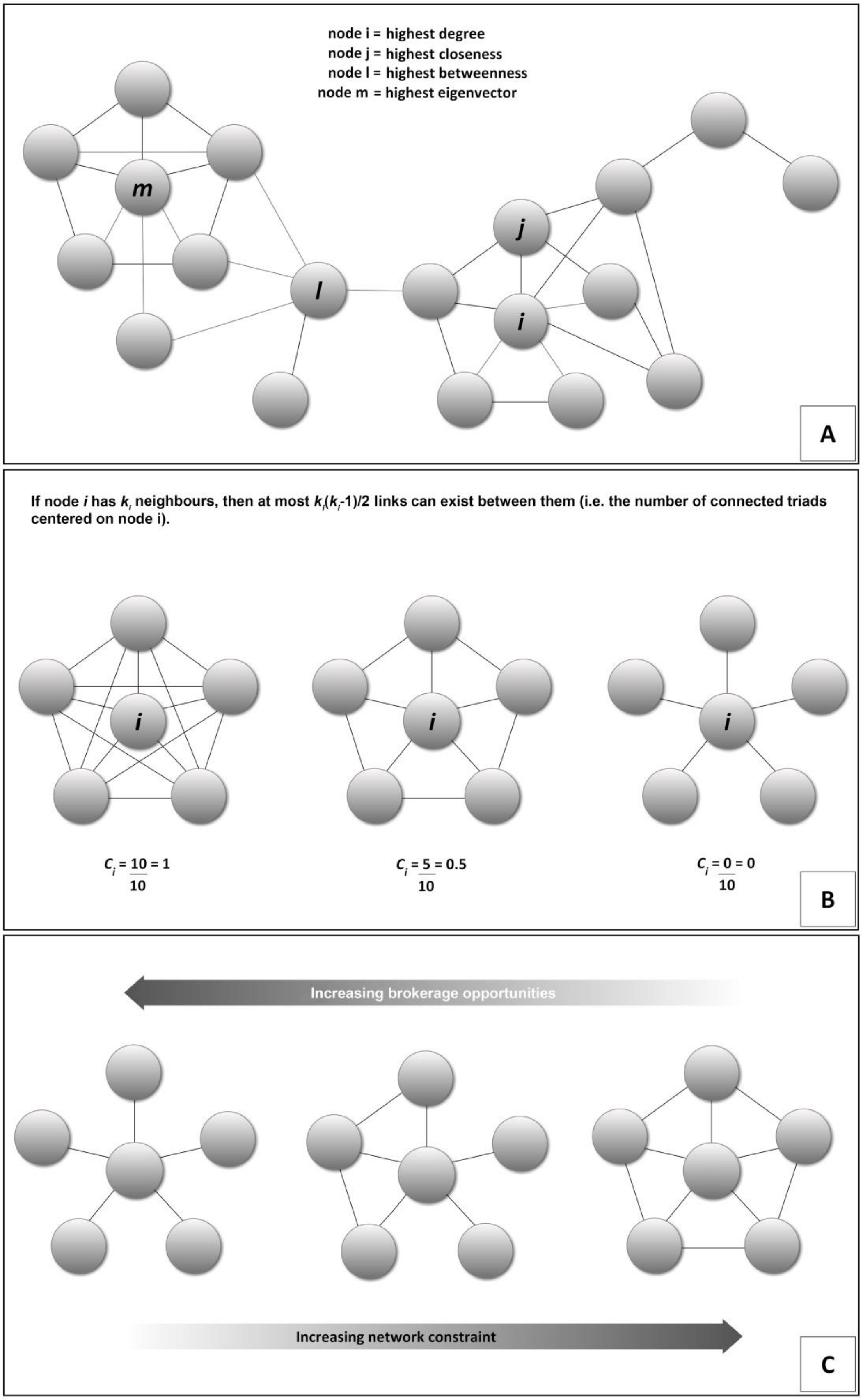
	Model 9		Model 10		Model 11		Model 12	
	EC	SE	EC	SE	EC	SE	EC	SE
Control variables								
Number of past publications	0.002**	0.000	0.003**	0.000	0.002**	0.001	0.001**	0.000
Gender	0.176*	0.077	0.142*	0.065	0.099	0.080	0.032	0.175
Physician status	-0.131	0.073	-0.227**	0.061	-0.238*	0.102	-0.420**	0.136
Senior lecturer	0.448*	0.207	0.276	0.214	0.436	0.310	0.231	0.323
Reader	0.531**	0.204	0.485*	0.222	0.781**	0.286	0.448	0.350
Professor	1.046**	0.193	0.796**	0.208	1.351**	0.298	0.391	0.315
Solo versus multi-authorship								
Solo authored articles	0.007	0.008	0.009	0.010	0.067**	0.021	0.015	0.009
Median number of co-authors per publication	0.028	0.016	0.039**	0.013	-0.017	0.024	0.032*	0.014
(Median number of co-authors per publication)^2	-0.003**	0.001	-0.002**	0.001	0.000	0.001	-0.002**	0.000
Minimum number of co-authors per publication	-0.076**	0.026	-0.065**	0.019	-0.035	0.025	-0.053**	0.019
Network-based measure of centrality								
Degree	6.837**	1.254	14.151**	1.318	7.780**	2.117	2.104*	0.829
Network-based measure of social capital								
Constraint	-1.000**	0.267	-0.785**	0.217	-0.582	0.397	-1.440**	0.273
Author's position in publication								
Position in non-alphabetized byline:								
First	0.035**	0.011	0.070**	0.013	0.079**	0.015	0.035**	0.011
Last	-0.123**	0.048	-0.109*	0.050	-0.147*	0.070	0.019	0.066
Second	0.029*	0.014	0.041**	0.013	0.030	0.016	0.011	0.016
Penultimate	-0.008	0.009	0.004	0.009	-0.009	0.010	0.004	0.005
Other	0.028**	0.008	0.032**	0.008	0.003	0.011	0.030**	0.005
Position in alphabetized byline:								
First	0.002	0.035	0.019	0.050	0.082	0.084	0.206*	0.084
Last	0.011	0.020	0.028	0.023	0.002	0.045	0.032	0.023
Second	0.020	0.040	0.095	0.049	0.062	0.068	0.102*	0.050
Penultimate	0.016	0.133	-0.128	0.131	-0.175	0.190	-0.059	0.097
Other	0.051	0.142	0.059	0.156	0.329*	0.152	0.012	0.173
Interactions: academic rank and position								
Senior lecturer X non-alphabetical last position	0.194	0.104	0.091	0.052	0.079	0.074	-0.012	0.071
Reader X non-alphabetical last position	-0.047	0.086	0.087	0.053	0.136	0.074	-0.018	0.071
Professor X non-alphabetical last position	0.046	0.048	0.164**	0.050	0.198**	0.069	0.012	0.066
Senior lecturer X alphabetical first position	-0.007	0.218	0.224*	0.108	0.106	0.137	-0.107	0.111
Reader X alphabetical first position	0.082	0.150	-0.027	0.083	-0.070	0.122	-0.199*	0.093
Professor X alphabetical first position	0.200**	0.049	-0.010	0.058	-0.047	0.098	-0.157	0.088
Interactions: academic rank, position, and brokerage								
Senior lecturer X non-alphabetical last position X constraint			-0.199**	0.067	-0.106	0.202	-0.263	0.157
Reader X non-alphabetical last position X constraint			0.291*	0.137	-0.002	0.230	0.025	0.155
Professor X non-alphabetical last position X constraint			0.331**	0.051	0.263*	0.126	0.222**	0.057
Time period 1							1.104**	0.060
Time period 2							0.877**	0.041
Number of observations	1285		1285		1285		1257	
Number of groups	490		490		490		463	
Wald chi square	1868.340		1453.110		586.790		2149.850	
Prob > ChiSq	0.000		0.000		0.000		0.000	
Log pseudolikelihood					-70132.897		-4574.788	

EC = estimated coefficient; SE = standard error
* p < 0.05, ** p < 0.01

Appendix Table S6b Estimated parameters from various regression models. Model 9 is the GEE Poisson estimator with equicorrelated errors. Model 10 is the GEE negative binomial estimator with equicorrelated errors. Model 11 is the Poisson maximum likelihood panel estimator with gamma-distribued random effects and cluster-robust bootstrapped standard errors (100 replications). Model 12 is the conditional maximum likelihood fixed-effects negative binomial panel estimator with both individual- and time-specific effects and cluster-robust boostrapped standard errors (100 replications). Unlike tables 3 and S5, this table reports Poisson or negative binomial (unexponentiated) estimated coefficients.



Appendix Figure S1 The largest connected component (13) of academics from the Faculty of Imperial College Medicine extracted from the entire co-authorship network. Academic rank is indicated by shape (circle = lecturer, triangle = senior lecturer, square = reader, trapezius = professor). The size of each node is proportional to the academic's citation count. Node color is determined by h-index (red = max, blue = min).



Appendix Figure S2 Examples of network measures of centrality and social capital

REFERENCES

1. Patel VM, Ashrafian H, Bornmann L, Mutz R, Makanjuola J, Skapinakis P, et al. Enhancing the h index for the objective assessment of healthcare researcher performance and impact. Journal of the Royal Society of Medicine. 2013;106(1):19-29.
2. Imperial College London: http://www1.imperial.ac.uk/medicine/about/. 2011.
3. National Academy of Sciences, National Academy of Engineering, Institute of Medicine, Committee on Maximizing the Potential of Women in Academic Science and Engineering. Beyond bias and barriers: Fulfilling the potential of women in academic science and engineering. Washington, DC: National Academies Press; 2006.
4. Elsevier. Scopus Website: http://www.scopus.com. 2004.
5. Aksnes DW. Citation rates and perceptions of scientific contribution. Journal of the American Society for Information Science and Technology. 2006;57(2):169-85.
6. Bornmann L, Daniel HD. What do citation counts measure? A review of studies on citing behavior. J Docum. 2008;64:45-80.
7. Radicchi F, Fortunato S, Castellano C. Universality of citation distributions: toward an objective measure of scientific impact. Proceedings of the National Academy of Sciences of the United States of America. 2008 Nov 11;105(45):17268-72. PubMed PMID: 18978030. Pubmed Central PMCID: 2582263.
8. Penner O, Pan RK, Petersen AM, Kaski K, Fortunato S. On the predictability of futre impact in science. Scientific Reports. 2014;3(3052):doi:10.1038/srep03052.
9. Petersen AM, Fortunato S, Pan RK, Kaski K, Penner O, Rungi A, et al. Reputation and impact in academic careers. Proceedings of the National Academy of Sciences of the United States of America. 2014 Oct 6;111(43):15316-21. PubMed PMID: 25288774.
10. Wootton R. A simple, generalizable method for measuring individual research productivity and its use in the long-term analysis of departmental performance, including between-country comparisons. Health research policy and systems / BioMed Central. 2013;11:2. PubMed PMID: 23317431. Pubmed Central PMCID: 3560253.
11. NWB Team. Network Workbench Tool. Indiana University, Northeastern University, and University of Michigan, 2006.
12. Newman MEJ. The structure of scientific collaboration networks. Proceedings of the National Academy of Sciences of the United States of America. 2001 Jan 16;98(2):404-9. PubMed PMID: 11149952. Pubmed Central PMCID: 14598.
13. Newman MEJ. Networks: An Introduction. Oxford: Oxford University Press; 2010.
14. Brandes U, Wagner D. Visone - Analysis and visualization of social networks. In: Jünger M, Mutzel P, editors. Graph drawing software: Springer-Verlag; 2004. p. 321-40.
15. Wasserman S, Faust K. Social Network Analysis: Methods and Applications New York: Cambridge University Press; 1994.
16. Watts DJ, Strogatz SH. Collective dynamics of 'small-world' networks. Nature. 1988;393:440-2.
17. Burt RS. Structural Holes. The Social Structure of Competition. Cambridge, MA: Harvard University Press; 1992.
18. Freeman LC. A set of measures of centrality based upon betweenness. Sociometry. 1977;40:35-41.
19. Ahuja G. Collaboration networks, structural holes, and innovation: A longitudinal study. Administrative Science Quarterly. 2000;45:425-55.

20. Perry-Smith JE, Shalley CE. The social side of creativity: A static and dynamic social network perspective. Academy of Management Review. 2003;28(1):89-106.
21. Bonacich PF. Power and centrality: A family of measures. American Journal of Sociology. 1987;92:1170-82.
22. Coleman JS. Social capital in the creation of human capital. American Journal of Sociology. 1988;94:S95-S120.
23. Latora V, Nicosia V, Panzarasa P. Social cohesion, structural holes, and a tale of two measures. Journal of Statistical Physics 2013;151(3):745-64.
24. Burt RS. Structural holes and good ideas. American Journal of Sociology. 2004;110:349-99.
25. Granovetter M. The strength of weak ties. American Journal of Sociology. 1973;78:1360-80.
26. Tscharntke T, Hochberg ME, Rand TA, Resh VH, Krauss J. Author sequence and credit for contributions in multiauthored publications. PLoS biology. 2007 Jan;5(1):e18. PubMed PMID: 17227141. Pubmed Central PMCID: 1769438.
27. Laband DN, Tollison RD. Intellectual collaboration. Journal of Political Economy. 2000;108(3):632-62.
28. Waltman L. An empirical analysis of the use of alphabetical authorship in scientific publishing. Journal of Informetrics. 2012;6(4):700-11.
29. Riesenberg D, Lundberg GD. The order of authorship: Who's on first. Jama. 1990;264(14):1857.
30. He B, Ding Y, Yan E. Mining patterns of author orders in scientific publications. Journal of Informetrics. 2012;6(3):359-67.
31. Chambers R, Boath E, Chambers S. The A to Z of authorship: analysis of influence of initial letter of surname on order of authorship. Bmj. 2001;323 (7327):1460-1.
32. Savitz DA. What can we infer from author order in epidemiology? Am J Epidemiol. 1999;149(5):401-3.
33. Good IJ. Order of authorship. American Statistician. 1989;42(4):288-9.
34. Joseph K, Laband DN, Patil V. Author order and research quality. Southern Economic Journal. 2005;71(3):545-55.
35. Einav L, Yariv L. What's in a surname? The effects of surname initials on academic success. The Journal of Economic Perspectives. 2006;20(1):175-87.
36. Rudd E. Effect of alphabetical order of author listing on careers of scientists. Social Studies of Science. 1977;7(2):268-9.
37. Cameron AC, Trivedi PK. Regression Analysis of Count Data. Cambridge: Cambridge University Press; 1998.
38. Cameron AC, Trivedi PK. Microeconometrics: Methods and Applications. New York: Cambridge University Press; 2005.
39. Heckman J. Studies in labor markets. In: Rosen S, editor. Heterogeneity and State Dependence. Chicago: University of Chicago Press; 1981. p. 91-139.
40. Hsiao C. Analysis of Panel Data. Cambridge: Cambridge University Press; 2003.