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Performance-Related Differences of Bibliometric Statistical Properties of Research Groups: Cumulative Advantages and Hierarchically Layered Networks

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In this article we distinguish between top-performance and lower-performance groups in the analysis of statistical properties of bibliometric characteristics of two large sets of research groups. We find intriguing differences between top-performance and lower-performance groups, and between the two sets of research groups. These latter differences may indicate the influence of research management strategies. We report the following two main observations: First, lower-performance groups have a larger size-dependent cumulative advantage for receiving citations than top-performance groups. Second, regardless of performance, larger groups have fewer not-cited publications. Particularly for the lower-performance groups, the fraction of not-cited publications decreases considerably with size. We introduce a simple model in which processes at the microlevel lead to the observed phenomena at the macrolevel. Next, we fit our findings into the novel concept of hierarchically layered networks. In this concept, which provides the "infrastructure" for the model, a network of research groups constitutes a layer of one hierarchical step higher than the basic network of publications connected by citations. The cumulative size advantage of citations received by a group resembles preferential attachment in the basic network in which highly connected nodes (publications) increase their connectivity faster than less connected nodes. But in our study it is size that causes an advantage. In general, the larger a group (node in the research group network), the more incoming links this group acquires in a nonlinear, cumulative way. Nevertheless, top-performance groups are about an order of magnitude more efficient in creating linkages (i.e., receiving citations) than lower-performance groups. This implies that together with the size-dependent mechanism, preferential attachment, a quite common characteristic of complex networks, also works. Finally, in the framework of this study on performance-related differences of bibliometric properties of research groups, we also find that top-performance groups are, on average, more successful in the entire range of journal impact.

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Introduction

In a recent paper (van Raan, 2006a) we presented an empirical approach to the study of the statistical properties of bibliometric indicators on a very relevant but not simply "available" aggregation level: the research group. Research groups are defined by the internal structure of universities, research institutions, and research and development (R&D) laboratories of companies. They are not an entity directly available in databases as in the case of authors or journals. The focus of our previous study was on the distribution functions of a coherent set of indicators frequently used as a measuring instrument in the analysis of research performance, in order to provide a better insight into the statistical properties of the instrument.

Starting with the most basic statistical element in bibliometric analysis, the very skew distribution of citations over publications, we clearly observed in our previous study the working of the central limit theorem. We found that at the level of research groups the distribution functions of the main indicators, particularly the journal-normalized and the field-normalized indicators, are approaching normal distributions. The results underlined the importance of the idea of "group oeuvre," i.e., the role of sets of *organizationally* related publications as a unit of analysis. We noticed that organizationally related publications differ from *bibliometrically* related (i.e., coauthor-related or citation-related) publications. These latter types of relations are the basis of practically all publication data–based networks in current network studies.

In our previous study the focus was on the statistical properties of large sets of research groups as a whole. Now we want to go one step further. We will distinguish between *top-* and *lower-performance* groups within these large sets in order to study the differences in statistical properties in relation to performance. In particular, we are interested in the phenomenon of size-dependent (size of a research group in

terms of number of publications) *cumulative advantage*[1] of impact (in terms of numbers of citations), for different levels of research performance. As will be discussed, characteristics of this phenomenon suggest a model to explain the observations.

Katz (1999, 2000, 2005) discussed scaling relationships between number of citations and number of publications across research fields, institutes, and countries. He concluded that the scientific community is characterized by cumulative advantage, more particularly a size-dependent Matthew effect (Merton, 1968, 1988). As explained in footnote 1,[1] this implies a nonlinear increase of impact with increasing size, demonstrated by the finding that the number of citations as a function of number of publications (in Katz's study for 152 fields of science) exhibits a power-law dependence with an exponent larger than 1. In our previous paper we showed that *there also exists at the level of research groups* a size-dependent cumulative advantage of the correlation between number of citations and number of publications (see van Raan, 2006a).

From a general viewpoint it is important to study size-dependent characteristics of a network-based system (such as science) that is basically described by fractal (power-law distribution) properties. More specifically, often the scientific communication system is described as a network of publications with a fractal topology (in terms of the in-degree distributions of the links between the publications as nodes in the network), and thus the system is considered to be "scale-free"[2] (Zitt, Ramanana-Rahary, & Bassecoulard, 2003, 2005; Zitt, 2005). We emphasize, however, that this scale-free property *only* applies to the network's degree distributions. Networks may have, and usually do have, scale and thus size dependences in other network properties (Newman, 2003a). Indeed, our observations indicate that size-dependent characteristics do exist in such a system, in the case of specific clusters of publications, namely, research groups.

In order to explain our observations on cumulative size advantage of impact received by a group as a function of performance, we introduce a simple model in which processes at the microlevel lead to the observed phenomena at the macrolevel. A novel concept, *hierarchically layered networks*, provides the "infrastructure" for the model. This network of research groups constitutes a layer of one hierarchical step higher than the basic network of publications connected by citations. This concept shows the significance of our findings for bibliometrics because it enables us to distinguish precisely between the earlier mentioned networks of *bibliometrically related* (i.e., coauthor-related or citation-related) publications and *organizationally related* publications.

In the framework of the present study we also investigated other performance-related differences of bibliometric properties of research groups. An important problem is the role of the journal impact level, with the potential for a journal-dependent cumulative advantage on the impact of research groups. The discussion on the meaning of journal impact for evaluation studies regularly flares up; a recent example is the discussion in *Nature*, initiated by a paper by Lawrence (2003), in which researchers, referring to the work of Seglen (1992, 1994), fulminate against the supposed dominant role of journal status and journal impact factors in the present-day life of a scientist. An important finding of Seglen was the poor correlation between the impact of publications and journal impact, both for the whole publication set as well as for individual authors, at *the level of individual publications*. However, grouping publications in classes of journal impact yielded a high correlation between publication and journal impact. But this higher aggregation is determined by journal impact classes, and not by a "natural" higher aggregation level such as a research group. In this study we show a significant correlation between the average number of citations per publication (publication citedness) of research groups and the average journal impact of these groups.

The structure of this study is as follows. Within a set of all 157 university chemistry groups in the Netherlands and a set of 65 medical research groups within a university, we distinguish in our analysis between *top-performance* and *lower*-performance groups. In Data Material and Bibliometric Indicators we discuss the data material of both sets of research groups, the application of the method, and calculation of indicators. In Results and Discussion we analyze the data of the research groups in the framework of size-dependent cumulative advantage and classify the results of the analysis in two main observations. Next, we construct a model to explain the observations and introduce the concept of hierarchically layered networks. Our analysis of performance-related differences of bibliometric properties of research groups reveals further interesting results, particularly on the role of journal impact. These observations are discussed in the last part of Results and Discussion. Finally, in Summary of the Main Findings and Concluding Remarks we summarize the main outcomes of this study.

[1]By *cumulative advantage* we mean that the dependent variable (for instance, number of citations of a group, C) increases in a disproportional, nonlinear (in this case: power law) way as a function of the independent variable (for instance, in the present study the size of a research group, in terms of number of publications, P). Thus, larger groups (in terms of P) not only receive more citations (as can be expected), but do so increasingly more advantageously: groups that are twice as large as other groups receive, on average, about 2.4 more citations. There is an interesting relation between the concept of cumulative advantage by size and the Cobb-Douglas production function in mathematical economics. We refer to Appendix B for further discussion.

[2]Fractal (power-law) distributions $P(x) = kx^{\gamma}$(k is a constant; γ is the power-law exponent, always negative in the case of distribution functions) are scale-free: that is, these functions remain unchanged under *rescaling of the independent variable x*. Thus $P(ax) = bP(x)$, where a and b are constants. Proof: $P(ax) = k(ax)^{\gamma} = a^{\gamma}kx^{\gamma} = a^{\gamma}P(x) \rightarrow a^{\gamma} = b$. This property is often associated with complex systems that have grown to a steady state where growth rates do not depend on scale. For instance, $P(x)$ is the distribution function of the number of events such as earthquakes, scientific discoveries, publications with variable x (e.g., impact).

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Data Material and Bibliometric Indicators

The Two Data Sets

We studied the statistics of bibliometric indicators on the basis of two large sets of publications (only journals covered by the *Citation Index*; publications in these journals are designated as *CI publications*).[3] The first set covers all academic chemistry research in a country (Netherlands) for a 10-year period (1991–2000). The second set covers all research groups in a large medical faculty (Leiden University) for a period of 12 years. This material is quite unique. To our knowledge no such compilations of very accurately verified publication sets on a large scale are used for statistical analysis of the characteristics of the indicators at the research group level.

We stress again that the research group is the most important work floor entity in science. However, obtaining data at the research group level is not a trivial matter. Data on the level of the individual scientists are externally available (such as *CI* data on author names, addresses, journals, fields, citations), but this is not the case at the level of research groups. The only possibility for studying bibliometric characteristics of research groups with "external data" would be to use the address information within the main organization, for instance, "Department of Biochemistry" of a specific university. However, the delineation of departments or university groups through externally available data such as the address information in the *CI* database is very problematic. For a thorough discussion of this problem, see Van Raan (2005b). Furthermore, the external data have to be combined carefully with "internally stored" data (such as personnel belonging to specific groups). These data are only available from the institutions that are the target of the analysis. As indicated previously, the data used in this study are the results of evaluation studies and are therefore based on strict verification procedures in close collaboration with the evaluated groups.

The first set concerns all journal articles of all university research groups in chemistry and chemical engineering in the Netherlands (NL). Thus, publications such as reports and books or book chapters are not taken into account. However, for chemistry research groups the focus on papers published in *CI*-covered journals generally provides a very good representation of the scientific output (VSNU, 2002). These (CI) publications were collected as part of a large evaluation study conducted by the VSNU, the Association of Universities in the Netherlands. For a detailed discussion of the evaluation procedure and the results we refer to the evaluation report (VSNU, 2002). In the framework of this evaluation study, we performed an extensive bibliometric analysis to support the evaluation work of an international peer committee (van Leeuwen, Visser, Moed, & Nederhof, 2002). The period covered is 1991–2000 for both publications and citations received by these publications. In total, the analysis involves 700 senior researchers and covers about 18,000 publications and 175,000 citations (excluding self-citations) of 157 chemistry groups.

The indicators are calculated on the basis of a total time-period analysis. This means that publications are counted for the entire 10-year period (1991–2000) and citations are counted up to and including 2000 (e.g., for publications from 1991, citations are counted in the period 1991–2000, and for publications from 2000, citations are counted only in 2000). The universities covered by this evaluation study are Leiden, Utrecht, Groningen, Amsterdam UvA, Amsterdam VU, Nijmegen, Delft, Eindhoven, Enschede (Twente), and Wageningen. All fields of chemistry were covered by this set of university groups; the main fields were analytical chemistry, spectroscopy, and microscopy; computational and theoretical chemistry; physical chemistry; catalysis; inorganic chemistry; organic and bioorganic chemistry; biochemistry, microbiology, and biochemical engineering; polymer science and technology; materials science; and chemical engineering.

The second set concerns all publications (again, those published in journals covered by the *Citation Index*, designated *CI publications*) of all research groups in the Leiden University Medical Center (LUMC).[4] In this case, too, the focus on papers published in *CI*-covered journals generally provides a very good representation of the scientific output. These publications were collected as part of an internal Leiden evaluation study. In the framework of this evaluation study, we performed a detailed bibliometric analysis to support the LUMC research evaluation board. Details of the results are available from the author of this article. The period covered is 1990–2001 for both publications and the citation received by these publications. The citation counting procedure is the same as for the chemistry groups. In total, the analysis involves 400 senior researchers and covers about 10,000 publications and 185,000 citations (excluding self-citations) of 65 medical groups.

The Bibliometric Analysis and Applied Indicators

We apply the CWTS (Centrum voor Wetenschaps-en Technologiestudies, Center for Science and Technology Studies) standard bibliometric indicators. Here only "external" citations, i.e., citations corrected for self-citations, are taken into account. An overview of these indicators is given in Appendix A. In particular, we draw attention to the definition of our journal impact indicator, *JCSm*. For a detailed discussion refer to Van Raan (1996, 2004, 2005c).

[3]Thomson Scientific, the former Institute for Scientific Information (ISI) in Philadelphia, is the producer and publisher of the *Web of Science* and the *Science Citation Index*, the *Social Science Citation Index*, the *Arts & Humanities Citation Index*, and the specialty citation indexes (*CompuMath*, *Biochemistry and Biophysics*, *Biotechnology*, *Chemistry*, *Material Science*, *Neurosciences*). Throughout this article we use the acronym *CI* (*Citation Index*) to refer to this set of databases.

[4]The LUMC is a large clinical and basic research institute (medical faculty) of high international reputation. Practically all fields of medical research are present, ranging from molecular cell biology to oncological surgery, and from organ transplantation to T-cell immune response research.

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TABLE 1. Example of the results of the bibliometric analysis for the chemistry groups.

Research group	*P*	*C*	*CPP*	*JCSm*	*FCSm*	*CPP/JCSm*	*CPP/FCSm*	*JCSm/FCSm*	Quality
Univ A, 01	92	554	6.02	5.76	4.33	1.05	1.39	1.33	5
Univ A, 02	69	536	7.77	5.12	2.98	1.52	2.61	1.72	4
Univ A, 03	129	3,780	29.30	17.20	11.86	1.70	2.47	1.45	5
Univ A, 04	80	725	9.06	8.06	6.25	1.12	1.45	1.29	4
Univ A, 05	188	1,488	7.91	8.76	5.31	0.90	1.49	1.65	5
Univ A, 06	52	424	8.15	6.27	3.56	1.30	2.29	1.76	4
Univ A, 07	52	362	6.96	4.51	5.01	1.54	1.39	0.90	3
Univ A, 08	171	1,646	9.63	6.45	4.36	1.49	2.21	1.48	5
Univ A, 09	132	2,581	19.55	15.22	11.71	1.28	1.67	1.30	4
Univ A, 10	119	2,815	23.66	22.23	14.25	1.06	1.66	1.56	4
Univ A, 11	141	1,630	11.56	17.83	12.30	0.65	0.94	1.45	4
Univ A, 12	102	1,025	10.05	10.48	7.18	0.96	1.40	1.46	5

TABLE 2. Example of the results of the bibliometric analysis for the medical groups.

Research group	*P*	*C*	*CPP*	*JCSm*	*FCSm*	*CPP/JCSm*	*CPP/FCSm*	*JCSm/FCSm*	*Pnc*	*Scit*
LU 01	117	1,836	15.69	12.20	11.08	1.29	1.42	1.10	11%	20%
LU 02	197	3,587	18.21	14.28	14.75	1.28	1.23	0.97	11%	21%
LU 03	46	449	9.76	14.55	8.78	0.67	1.11	1.66	20%	23%
LU 04	560	16,906	30.19	25.22	15.29	1.20	1.97	1.65	10%	19%
LU 05	423	17,144	40.53	29.60	16.85	1.37	2.41	1.76	6%	21%
LU 06	369	13,454	36.46	30.34	17.54	1.20	2.08	1.73	6%	19%
LU 07	91	1,036	11.38	11.91	7.72	0.96	1.47	1.54	15%	22%
LU 08	95	554	5.83	6.52	5.80	0.89	1.01	1.13	22%	33%
LU 09	52	334	6.42	6.98	8.00	0.92	0.80	0.87	23%	33%
LU 10	512	5,729	11.19	8.70	6.44	1.29	1.74	1.35	22%	17%

In Table 1 we show as an example the results of our bibliometric analysis for the most important indicators for all 12 chemistry research groups of one of the 10 universities ("Univ A"). The quality judgment *Q* of the international peer committee is also indicated. The peers used a 3-point scale to judge the research quality of a group: grade 5 is excellent, grade 4 is good, and grade 3 is satisfactory (VSNU, 2002).

We applied the same bibliometric indicators to the medical research groups. An example of the results (first 10 groups) is presented in Table 2. Thus, the results of both cases are based on a strictly consistent methodology, and therefore they are directly comparable. In the case of LUMC, however, we used a somewhat longer period (12 years) as compared to that in the chemistry case (10 years). The LUMC research evaluation board did not call in an international peer committee, so no quality judgment data as in the case of the chemical research groups are available. We added two further standard indicators, the percentage of not-cited publications (*Pnc*) and the percentage of self-citations (*Scit*).

Tables 1 and 2 make clear that our indicator calculations allow a statistical analysis of these indicators for both sets of research groups. Of the indicators, we regard the internationally standardized (field-normalized) impact indicator *CPP/FCSm* as our "crown" indicator. This indicator enables us to observe immediately whether the performance of a research group is significantly far below (indicator value < 0.5), below (0.5–0.8), around (0.8–1.2), above (1.2–1.5), or far above (>1.5) the international (Western world–dominated) impact standard of the field. Particularly with a *CPP/FCSm* value above 1.5, groups can be considered as scientifically strong. A value above 2 indicates a very strong group and groups with values above 3 can generally be considered really excellent and comparable to top groups at the best U.S. universities (van Raan, 1996, 2000, 2004).

The *CPP/FCSm* indicator generally correlates well with the quality judgment of peers. Studies of larger-scale evaluation procedures in which empirical material is available with data on both peer judgment as well as bibliometric indicators are quite rare. For notable exceptions, see Rinia, van Leeuwen, van Vuren, and van Raan (1998, 2001). Our analysis primarily deals with the following indicators: *P*, *C*, *CPP*, *JCSm*, *CPP/FCSm*, and *Pnc*.

Particularly for the present study, the sets of chemistry and medical groups differ in relevant aspects. The chemistry groups are from 10 different universities, they have grown more or less "naturally," and they are not subject to one specific research policy strategy as all 10 universities have their own priorities. The medical groups, however, are all within one large institution. Although they also can be considered as having a "natural" basis as a research group around one or two full professors, these groups are at the same time influenced by the policy of the LUMC as a whole. For instance,

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close mutual collaboration and the availability of the best people and facilities of a wide range of groups in the same location may enhance performance.

Results and Discussion

Size-Dependent Cumulative Advantage of Impact

In our previous study (van Raan, 2006a), we showed how a specific collection of publications (research group) is characterized in terms of the correlation between size (the total number of publications P of a specific research group)[5] and the total number of citations received by this group in a given period, C. This relation for all 157 chemistry research groups is presented in Figure 1a, and for the 65 medical research groups in Figure 1b. These figures show that this relation *on the aggregation level of research groups* is described with reasonable significance (coefficient of determination[6] of the fitted regression is $R^2 = 0.69$ and 0.86, respectively) by a power law:

- $C(P) = 2.31\ P^{1.25}$ for the chemistry research groups
- $C(P) = 0.56\ P^{1.60}$ for the medical research groups

We observe that the size of groups leads to a cumulative advantage (with exponent +1.25 and +1.60, respectively) for the number of citations received by these groups. Thus the assumption of Katz (1999, 2000) discussed earlier, that the Matthew effect (Introduction) also works in a sufficiently large set of research groups, is confirmed. But a remarkable further finding is that this size-dependent cumulative advantage is considerably larger for the LUMC groups. These groups differ from the chemistry groups in organizational aspects that may enhance performance. Further study is necessary to find out whether these differences are also related to disciplinary characteristics.

We further observe that the coefficients of the two preceding equations are quite different (2.31 and 0.56, respectively). Strictly speaking, this would mean that one chemistry publication could be expected to receive 2.3 citations, and one medical publication 0.6 citations. This phenomenon is a consequence of the empirical fact that the smallest medical groups appear to be less cited than the chemical groups of the same size (for $P = 10$ about a factor 2). But this difference rapidly changes in the opposite direction by the steeper slope of the regression line for the medical groups. Given the simple character of the present statistical analysis, devoted to determining cumulative advantage as a major property, and the rather "noisy" data in the lower P part (see Figure 1a and 1b),[7] we stress that the extrapolation to $P = 1$ cases is not very sensible.

In our previous study we stressed that in the context of research performance analysis studies, size-dependent "corrections" (on the basis of number of publications) of measured impact (on the basis of citations) will lead to an unreasonable leveling off of the impact indicators at the level of research

[5]The number of publications is a measure of size in the statistical context described in this article. It is, however, a proxy for the real size of a research group, for instance, in terms number of *staff full-time equivalents* (fte) available for research.

[6]In this study we are primarily interested in the broad characteristics of the data, particularly concerning cumulative advantage, and not in detailed statistical analysis, so we have used the statistical analysis procedures provided by Microsoft Excel 2000.

[7]To estimate the influence of these noisy data, we removed the 10 chemistry and 5 medical groups (Figure 1a and 1b, respectively) with the lowest P values from the correlation calculations. We found for the chemistry groups a coefficient value of 2.80 and an exponent value of 1.21 ($R^2 = 0.65$), and for the medical groups a coefficient value of 1.29 and an exponent value of 1.44 ($R^2 = 0.77$). So the error related to the noisiness of data remains, particularly for the exponents, within acceptable limits and does not substantially affect our findings.

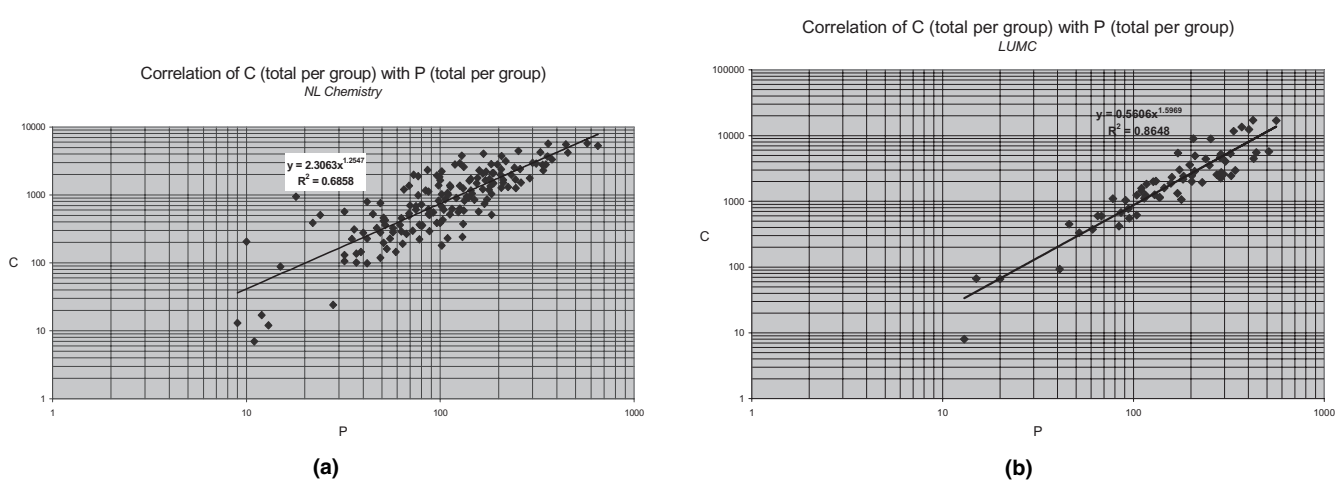

FIG. 1. (a) Correlation of the number of citations (C) received per research group with the number of publications (P) of these groups, for all chemistry groups. (b) Correlation of the number of citations (C) received per research group with the number of publications (P) of these groups, for all medical research (LUMC) groups.

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groups. This is because size can be regarded in many cases as an intrinsic characteristic of performance: top-research groups attract promising people, and thus these groups will have an advantage in terms of growth. It is therefore of crucial importance to investigate the preceding correlation for those subsets of the entire set that clearly represent *differences in research performance*. For the chemistry groups we have, next to the bibliometric indicators, the peer review results, as discussed in The Bibliometric Analysis and Applied Indicators.

We first created within the entire set of chemistry groups two subsets on the basis op the quality judgment by peers. In one subset with 39 top-performance groups, these groups received the highest judgment, excellent ($Q = 5$); and in another subset, with 30 lower-performance groups, these groups received the lowest judgment, satisfactory ($Q = 3$). The results are given in Figure 2.

We now make our first main observation: the striking difference between the two subsets. The top-performance groups generally have more total citations for a given size in terms of P. The cumulative advantage, however, is considerably less (in fact almost nonexistent, exponent 1.05) than for the lower-performance groups (exponent 1.42). Results for the subsets on the basis of our research performance indicator *CPP/FCSm* are presented in Figure 3 (a and b: top 10% and bottom 10%, chemistry and medical groups, respectively; c and d: top 20% and bottom 20% of the *CPP/FCSm* distribution, chemistry and medical groups, respectively; and e and f: top 50% and bottom 50%, chemistry and medical groups, respectively).

As expected, and similarly to the observations in Figure 2 based on peer-review quality ratings, we notice that the top-performance groups generally have more total citations for a given size in terms of P. Again, the cumulative advantage is considerably less for the top- than for the low-performance groups. Gradual differentiation between top and lower performance (top/bottom 10%, 20%, and 50%) enables us to study the correlation of C with P and possible scale effects (size-dependent cumulative advantage) in more detail. A summary of the results based on the observations in Figure 3(a–f) is presented in Table 3.

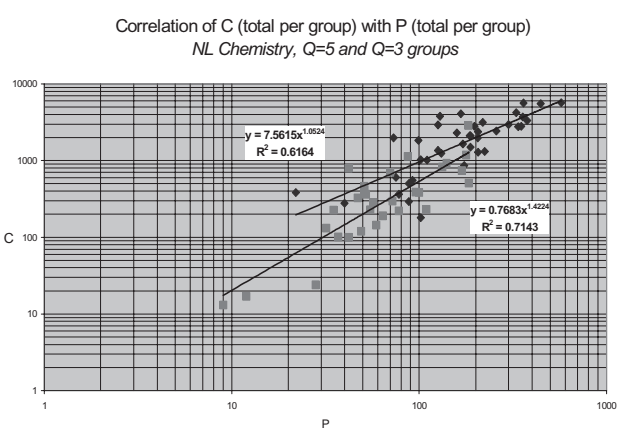

FIG. 2. Correlation of the number of citations (C) received per chemistry research group with the number of publications (P), for the top-performance groups ($Q = 5$, indicated with diamonds), and for the lower-performance groups ($Q = 3$, indicated with squares).

TABLE 3. Power-law exponent α of the correlation of C with P for the two sets of groups, in the indicated modalities. The differences in α between the set of chemistry research groups and the set of medical research groups is given by $\Delta\alpha$(M, C); the difference between the top and bottom modalities (see text) by $\Delta\alpha(b, t)$.

	Chemistry groups	Medical groups	$\Delta\alpha$(M, C)
Top 10%	0.72	1.13	*0.41*
Bottom 10%	1.44	1.75	*0.31*
$\Delta\alpha(b, t)$	*0.72*	*0.62*	
Top 20%	0.90	1.39	*0.49*
Bottom 20%	1.46	1.64	*0.18*
$\Delta\alpha(b, t)$	*0.56*	*0.25*	
Top 50%	1.06	1.54	*0.48*
Bottom 50%	1.44	1.55	*0.11*
$\Delta\alpha(b, t)$	*0.38*	*0.01*	

The results of this first observation are quite amazing. We distinguish four specific elements in this observation. First, the medical research groups have a stronger advantage with size (P) than the chemistry groups, particularly for top-group research. For the "bottom" the difference in advantage $\Delta\alpha$(M, C) between medical and chemistry groups is smaller. Second, for the medical research groups the difference in advantage between top- and bottom-groups $\Delta\alpha(b, t)$ is smaller than for the chemistry groups. Third, the top 10%, 20%, and 50% of the chemistry groups do not have a cumulative advantage (i.e., exponent significantly[8] > 1). For the medical research groups, the cumulative advantage is clearly visible in all modalities. Furthermore, the measured values of the correlation coefficients clearly show the large difference in impact between top- and low-performance groups (e.g., 57.3 versus 0.43, and 16.0 versus 0.15 in Figure 3a and b, respectively).

The fourth, and most intriguing element is, as mentioned, that for both the chemistry and the medical groups, the *bottom* groups profit *more* than the top groups (with the exception of the bottom 50% of the medical research groups). This latter phenomenon has the consequence that for a specific size (P), top 10% and bottom 10% have almost the

[8]To estimate the influence of the overall noisiness of the data, we randomly removed five groups from the correlation calculations of the top 20% and bottom 20% for the chemistry groups (Figure 3c). We found coefficient values of 25.6 and 0.43, and exponent (α) values of 0.85 and 1.50, for the top 10% ($R^2 = 0.58$) and bottom 20% ($R^2 = 0.81$), respectively. Again the error related to the noisiness of data remains, particularly for the exponents, within acceptable limits and does not substantially affect our findings. We estimate the error in the exponents α about ± 0.05, and the error in $\Delta\alpha$(M, C) and $\Delta\alpha(b, t)$ about ± 0.10.

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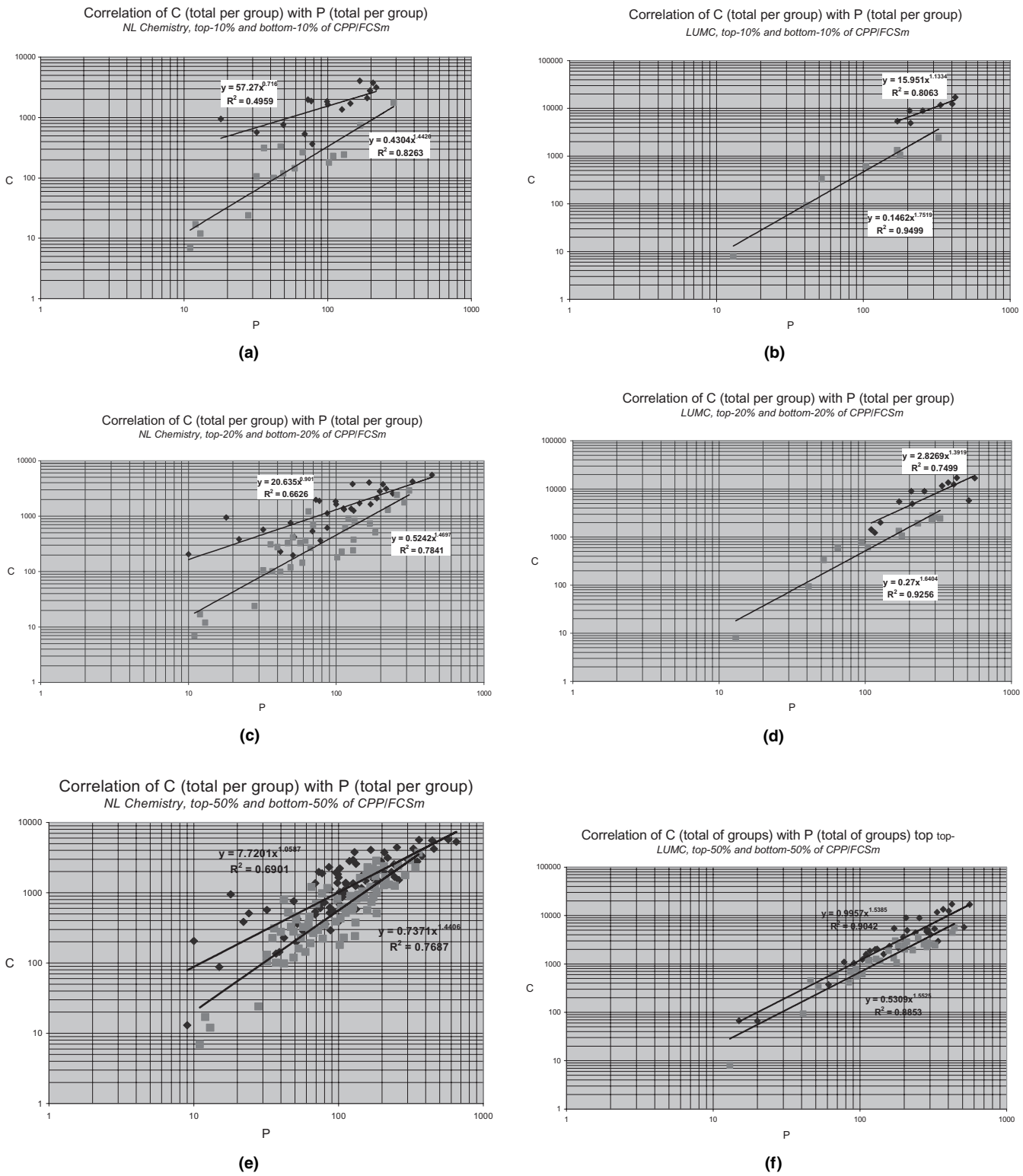

FIG. 3. (a) Correlation of the number of citations (*C*) received per chemistry research group with the number of publications (*P*), for the top 10% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 10% groups (indicated with squares). (b) Correlation of the number of citations (*C*) received per medical (LUMC) research group with the number of publications (*P*), for the top 10% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 10% groups (indicated with squares). (c) Correlation of the number of citations (*C*) received per chemistry research group with the number of publications (*P*), for the top 20% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 20% groups (indicated with squares). (d) Correlation of the number of citations (*C*) received per medical (LUMC) research group with the number of publications (*P*), for the top 20% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 20% groups (indicated with squares). (e) Correlation of the number of citations (*C*) received per chemistry research group with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 50% groups (indicated with squares). (f) Correlation of the number of citations (*C*) received per medical (LUMC) research group with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 50% groups (indicated with squares).

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same total citation impact (C); see, for instance, Figure 3e, from about $P = 400$. Research groups are active within a specific theme or subfield of a discipline; hence the total number of "available" citations will be "exhausted." Thus, a saturation of cumulative advantage is unpreventable simply because of finite-size considerations.

Modeling Advantages

In the previous section we discussed our first observation concerning cumulative advantages and, particularly, the most interesting finding so far: that *lower-performance* groups have a *larger* size-dependent cumulative advantage than top-performance groups. What is the significance of these findings for bibliometrics? To answer this question, we develop in this section a model in which we narrow down the previous general question to the core question: what does size actually do?

In an attempt to understand more precisely what is going on, we have to build a bridge between the "macro" picture given by the correlation between C and P at the level of groups and the "micro" picture, particularly the distribution of citations over publications $p(C)$ within a group. We use P to designate the total number of publications per group, p for the distribution function based on the number of "individual" publications, and pr for the distribution function with relative numbers of publications. Self-citations are excluded in this analysis.

Figure 4 shows the $pr(C)$ distribution for the largest 20% and the smallest 20% of the entire set of chemistry research groups. We stress that the subsets are *not* related to *differences in performance* (as in Figure 3a–f), but to *size differences*. Figure 4 reveals a crucial feature of the distribution. The subset of the smallest 20% has a significantly higher fraction of not-cited publications $pr(0)$ as compared to the subset of the largest 20%. The ratio for both subsets is 1.40. Thus, our second main observation is that *larger* groups have *fewer* not cited publications when compared to smaller groups. A direct consequence is that the largest 20% groups have relatively more publications with 2 to 20 citations, which represents a major part of the entire citation distribution. We suppose that a possible mechanism for cumulative advantage by group size works through decrease of the not-cited publications in a group and "promotion" of the already cited publications. In other words, size reinforces an internal promotion mechanism. We elaborate this idea later in this section.

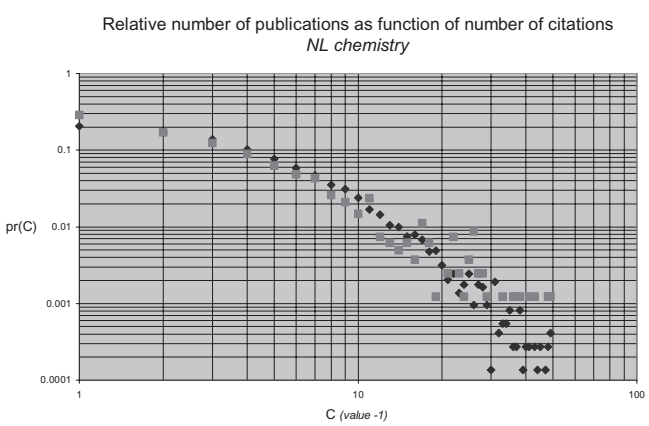

FIG. 4. Distribution function $pr(C)$: relative number of publications as a function of number of citations for two subsets within the total set of 157 chemistry publications. The subset of the groups that belong to largest 20% (diamonds) and the subset of the groups that belong to the smallest 20% (squares): in order to include $C = 0$ values in the logarithmic scale, we take on the abscissa value 1 for 0 citations, value 2 for 1 citation, etc.

As an additional empirical investigation of this observation for the medical research groups we analyzed the correlation of the fraction of not-cited publications Pnc of a group (given in Table 2) with the size (in terms of P) of a group. The results are shown in Figure 5a.

We observe, with low significance, that the fraction of not-cited publications decreases as a function of size in terms of number of publications in a group. This confirms the findings for the chemistry groups on the basis of the distribution functions. But the significance of the correlation is too low for clear results. Thus, as a further step we investigate the correlation of the fraction of not-cited publications Pnc of a group with size and with a distinction between top-performance groups and lower-performance groups similar to our analysis of the $C(P)$ correlation. The entire set of groups presented in Figure 5a is split into the top- and lower-performance groups. The results are presented in Figure 5b for the top 20% and bottom 20% and in Figure 5c for the top 50% and bottom 50%.[9]

The figures reveal several remarkable features. First, the LUMC top-performance groups are generally the larger ones, i.e., on the right-hand side of the correlation function (Figure 5b). The correlation is not significant for the top groups. Second, the lower-performance groups benefit from size, with reasonable significance for the bottom 10% and 20%. In other words, an important result of this study is that particularly for the lower-performance groups, with reasonable significance, the fraction of not-cited publications decreases with size.

Our explanation is that advantage by size works by a mechanism in which the number of not-cited publications is diminished, and that this mechanism is particularly effective for the lower-performance groups. We stress again that in our analysis self-citations are excluded!

Thus, the larger the number of publications in a group, the more those publications that otherwise would have remained uncited are "promoted." Thus, size reinforces an internal promotion mechanism. Most probably this works by initial citation of these "stay-behind" publications in other more cited publications of the group. Then authors in other groups are stimulated to take notice of these stay behind

[9]To prevent overloading this article with figures we leave out the top 10% and bottom 10% figures.

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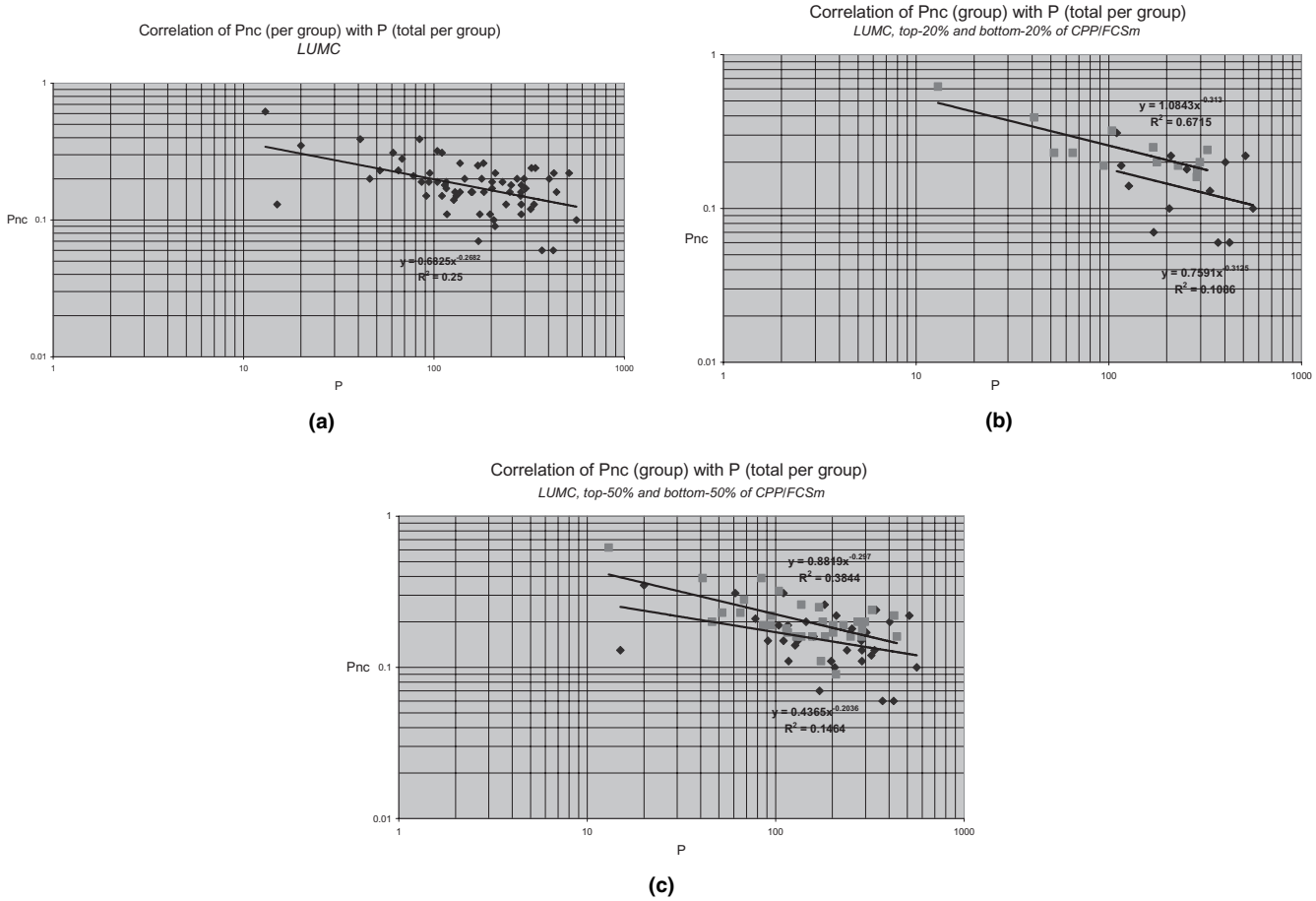

FIG. 5. (a) Correlation of the relative number of not-cited publications (*Pnc*) of the medical research groups with the number of publications (*P*). (b) Correlation of the relative number of not-cited publications (*Pnc*) of the medical research groups with the number of publications (*P*), for the top 20% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 20% groups (indicated with squares). (c) Correlation of the relative number of not-cited publications (*Pnc*) of the medical research groups with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 50% groups (indicated with squares).

publications, and they eventually decide to cite them. Consequently, the mechanism starts with within-group self-citation and subsequently spreads. It is obvious that particularly the lower-performance groups will benefit from this mechanism. Top-performance groups do not need the internal promotion mechanism to the same extent as low-performance groups. This explains, at least in a qualitative sense, why they show less, or even no cumulative advantage by size. Therefore, the group is a crucial entity; it is not "just a set of publications" (as is more or less the case for journals). The group represents the social structure in which the promotion mechanism can work.

The Concept of Hierarchically Layered Networks of Publications and Groups

Size-dependent cumulative advantages of research groups are interesting from the viewpoint of network analysis. The basic elements in our study of research groups are publications. Publications act as nodes in a citation network. Links indicate citations from other papers, so that the distribution of the number of citations represents the in-degree distribution of the network. These links are almost always

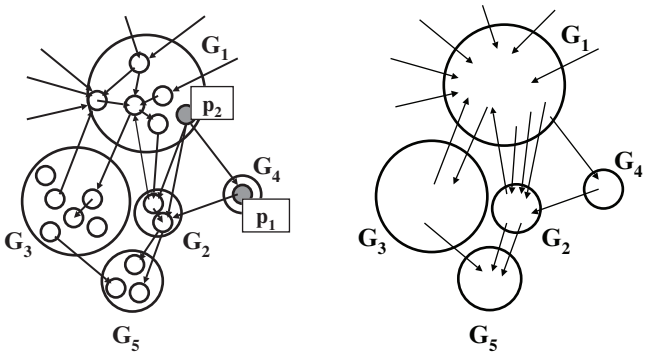

FIG. 6. Left: network structure (example) of individual publications with incoming links (citations to a publication, unidirectional); in-degree distribution is given by $p(C)$ (Figure 7a); right: same network structure now at the level of research groups (bidirectional links allowed); in-degree distribution is given by $G(C)$ (see Figure 7b).

unidirectional (see Figure 6). If publication p_1 is cited by publication p_2, publication p_2 cannot generally be cited by p_1.[10] In the present study, the in-degree distribution is given

[10]An exceptional case is, for instance, two publications published together in the same journal issue and citing each other mutually.

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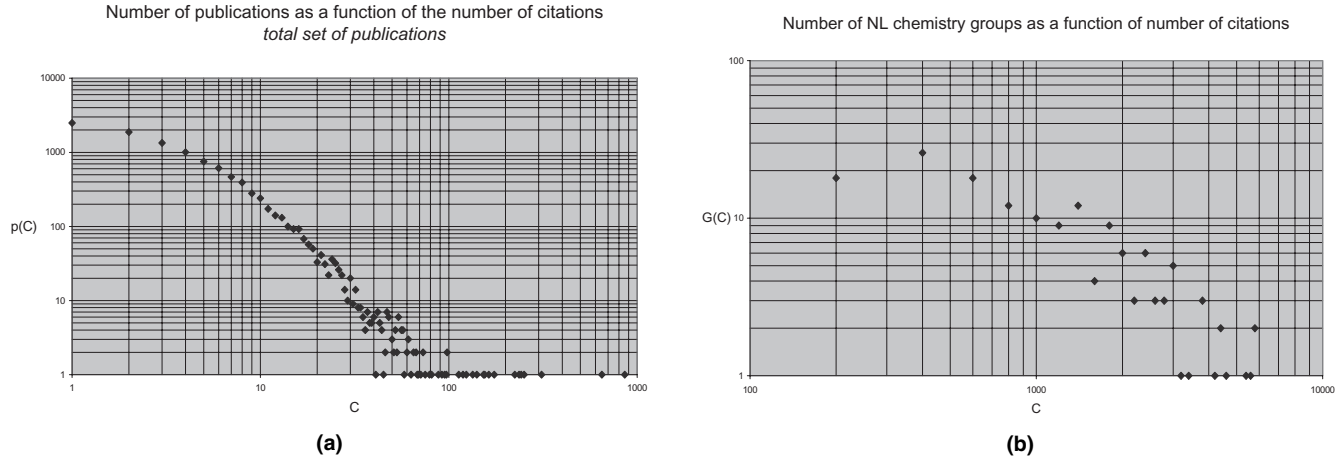

FIG. 7. (a) Distribution function $p(C)$: number of publications as a function of number of citations for the total set of around 14,000 chemistry publications. (b) Distribution function $G(C)$: number of groups as a function of number of citations per group, for the total set of the 157 chemistry research groups; groups are combined in classes of $\Delta C = 200$.

by $p(C)$; see Figure 7a. For a more detailed discussion of this distribution function, see van Raan (2006a).

In the last few years we have seen a considerable increase of attention in the physics community to publication- and citation-based networks (Albert & Barabási, 2002; Barabási & Albert, 1999; Dorogovtsev & Mendes, 2002; Mossa, Barthélémy, Stanley, & Amaral, 2002; Redner, 1998; Vazquez, 2001). More recently, the focus of the network community is moving toward clustering and preferential attachment phenomena in networks (Klemm & Eguíluz, 2002; Jeong, Néda, & Barabási, 2003; Newman, 2001; Ravasz & Barabási, 2003) and internetwork relations (Caldarelli, Erzan, & Vespignani, 2004).

Usually, *clustering* in a network is defined as a grouping of nodes on the basis of the linkages with which the network is structured. Examples are publication clusters based on citation or reference linkages (van Raan, 2005a) and clusters of collaborating researchers (Newman, 2003b). This type of clustering is *within* the network itself. The basic elements (nodes) of a network can, however, also be clustered in another structure *outside* their own network, for instance, in another network. Research groups can be seen as clusters of publications that represent a higher-order network based on organizational relations, i.e., a hierarchical layer above the network structured on the basis of individual publications. The group as a whole acts as a node in the network of research groups. These groups are also connected to each other through citation linkages, but in that case it is not important which individual publication is "responsible" for the incoming citations. In the context of this study, C is the number of incoming links to a group (in-degree of the group), and P is its size in terms of total number of publications of the group. In the example of Figure 6 we find $P = 6$ and $C = 8$ for group G_1. The distribution function of the number of groups over the number of incoming links, $G(C)$, is given in Figure 7b. So, in this model of hierarchically layered networks, we have the in-degree distribution of the basic network, i.e., the network of the individual publications represented by $p(C)$ (Figure7a), and the in-degree distribution of the hierarchically next layer (network of the groups) represented by $G(C)$ (Figure 7b).

There are striking differences between the higher-order network of groups and the basic publication network. First, in the basic network the nodes (publications) do not have a *size* (there is a node, or not). But in the group-based network the nodes (groups) do have a size, namely, the number of individual publications within a group. Second, the citation-based linkages at the group level are not *unidirectional* anymore (see Figure 6). If research group G_1 is cited by group G_2, the latter group can very well be cited by G_1, within a specific period. Third, in the basic network the nodes (i.e., the publications) can only have one link; i.e., publication p_1 is cited by publication p_2, and this happens only once, whereas research group G_1 can be cited many times by group G_2.

This third point introduces an interesting analogy with coauthor networks. Generally, networks of scientific collaboration based on coauthor relations are structured by linking authors who have at least one common publication. Nevertheless, authors can be linked to other authors by more than just one publication. Thus, authors will in fact have different linkage strengths with other authors, similar to the different citation linkage strengths G_1 has with G_2 (three citation links) and G_4 (one citation link) in Figure 6. The analogy goes further. Authors may differ substantially in the size of their own oeuvre, i.e., the number of papers they have, regardless of coauthors, for instance, the link between author a_1 (a senior scientist) who has many papers and three links with author a_2 (a Ph.D. student), who has only these three papers and just one link with another prolific author, a_3 (another senior scientist). In the usual scientific collaboration network a_1 is simply connected with one link to a_2 and with one link to a_3, without any indication of the size of a_1, a_2, and a_3. In reality we have a situation comparable with the

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example in Figure 6, the relation of the large group G_1 (like a_1) with the small group G_2 (like a_2), and G_1 with the other large group, G_3 (like a_3).

We stress that this phenomenon is not the same as preferential attachment (Newman, 2001, 2003a; Klemm & Eguíluz, 2002; Jeong et al., 2003). *Preferential attachment* means that highly connected nodes increase their connectivity more than less connected nodes: a *linkage-dependent* cumulative advantage. But in our study of research groups it is not the number of already existing links (C) but the size in terms of number of papers (P) that causes a preference: *a size-dependent* cumulative advantage. As discussed in Size-Dependent Cumulative Advantage of Impact, we find that the larger a group, the more, in a preferential, i.e., nonlinear, way (advantage) incoming links.

We also observe that the top 10% groups are about an order of magnitude more efficient in creating linkages (C) than the bottom 10% groups (see Figure 3a). As our criterion concerning top or low performance is based on the field-normalized indicator *CPP/FCSm*, we hypothesize that in network terms this indicator represents the *fitness* of a group as a node in the group network, which puts a group in a better position to acquire additional links on the basis of quality (high performance). In this sense the mechanism of preferential attachment clearly also works. Preferential attachment is based on the idea that other nodes, for instance, newcomers, feel the attractiveness (fitness) of a node and therefore also want to have a link with it. Thus, preferential attachment in the usual sense exists apart from the size-dependence advantage discussed. Very remarkably, this advantage is cumulative (exponent > 1) particularly for the bottom 10% groups. Thus, as explained in Size-Dependent Cumulative Advantage of Impact, for a specific size (P), top 10% and bottom 10% have almost the same strength (C) at the same size. The size of the node is crucial, with a simple advantage-making mechanism as explained by the model discussed in Modeling Advantages. In fact, the concept of hierarchically layered networks provides the infrastructure for this model.

The preceding discussion indicates the importance of a research group for scientists in bibliometric terms. Undoubtedly, the individual scientist and the individual paper remain crucial elements in the citation process, as authors do cite individual references for individual reasons. But as explained in Modeling Advantages, the group is, as it were, a "promotion facility" (by within-group self-citation) for publications within the group that would otherwise be unnoticed. The social structure of the group is the driving force of this promotion mechanism. This can be explained with an example. An individual scientist reads a paper (perhaps in a preprint stage) dealing with a topic that is not directly related to his or her own work but strongly related to important work of a colleague in the same group. The work of this colleague is, however, in spite of its evident importance, not mentioned. If the group is functioning well socially, the scientist will be stimulated to "promote" the colleague's work, for instance, in his or her role as a referee or in a forthcoming paper. Thus, next to the role of the individuals in the citation process, the research group acts as an additional, mediating actor in this process.

Size Dependence of Fitness

In the framework of the present study we also investigated other performance-related differences of bibliometric properties of research groups. We find no or hardly any significant dependence of our fitness indicator *CPP/FCSm* with size in terms of P, as shown in Figure 8a and 8b for the top 50% and the bottom 50% (of *CPP/FCSm* scores) of the chemistry and the medical research groups, respectively. Further analysis with the top and bottom 10% and the top and bottom 20%[11] reveals that only for the bottom 10% and 20% of the medical research groups is there a reasonably significant correlation with P ($R^2 = 0.55$ and 0.51, respectively). This indicates that for the lower-performance medical research groups there is some positive correlation with size. This, however, is certainly not a cumulative advantage. The exponents of the correlation are 0.14 and 0.15, respectively, more or less similar to the case of the bottom 50% of the medical research groups, as shown in Figure 8b.

We notice that for very large size P the value of *CPP/FCSm* must go asymptotically to 1, because the largest possible P would be all publications worldwide in a specific field, and therefore by definition the field-normalized indicator value has to be 1. Remarkably, in our observations onset of this asymptotic behavior is only slightly visible for the top groups in chemistry.

Publication Citedness and Journal Impact

An important problem is the role of the journal impact level, with potential for a journal-dependent cumulative advantage on the impact of research groups. Seglen (1994) showed that the citedness of individual publications is not significantly affected by journal status; therefore, "certain journals have a high impact simply because they publish high-impact articles." Seglen concluded that the use of journal impact as an indicator for research performance evaluation is inappropriate as the skewed distributions result in poor correlations between article citedness and journal impact. In his work, journal impact was restricted to the ISI journal impact factor only, and the more sophisticated types of journal impact indicators used in this study were not considered (Moed & Van Leeuwen, 1995, 1996).

We emphasize that Seglen reported on the poor correlation between the impact of publications and journal impact at *the level of individual publications*. However, grouping publications in classes of journal impact yielded a high correlation between publication citedness and journal impact. But this higher aggregation is determined by journal impact classes, and not by a "natural" higher aggregation level such as a research group.

[11]Figures not shown in this paper are available from the author.

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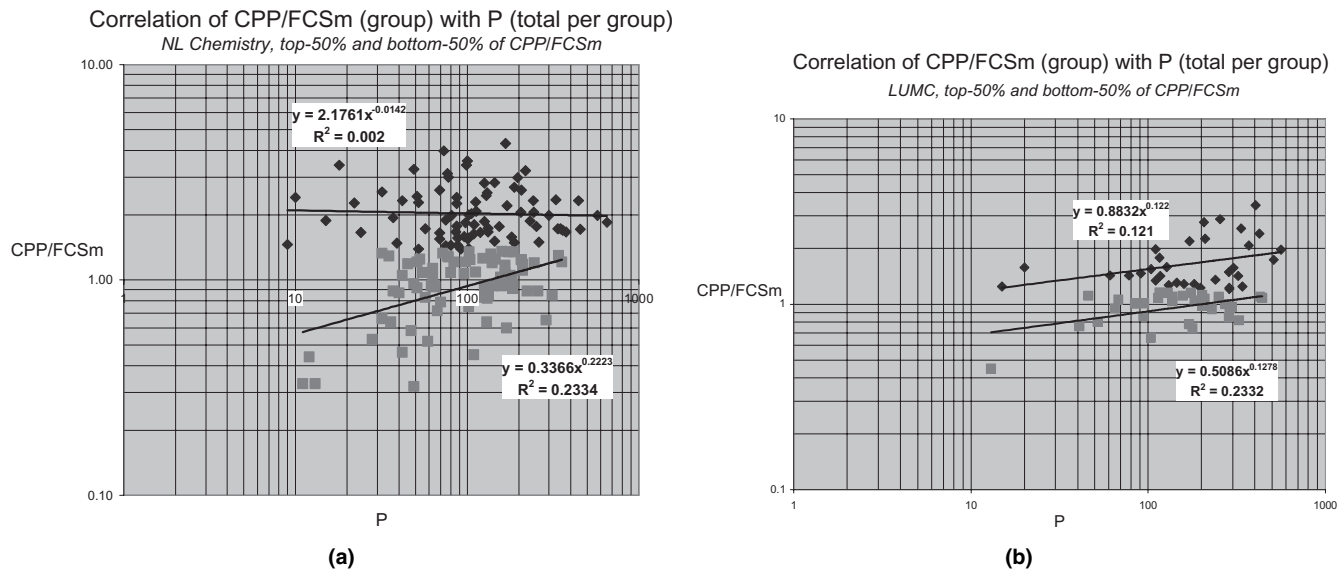

FIG. 8. (a) Correlation of *CPP/FCSm* with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) chemistry groups (indicated with diamonds), and for the bottom 50% chemistry groups (indicated with squares). (b) Correlation of *CPP/FCSm* with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) medical research groups (indicated with diamonds), and for the bottom 50% medical research groups (indicated with squares).

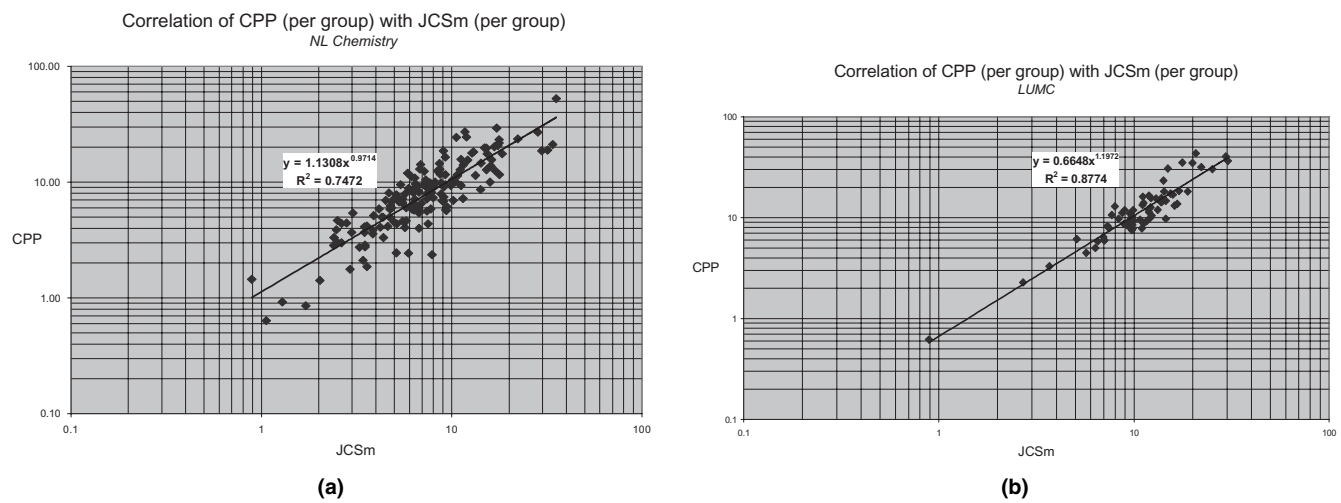

FIG. 9. (a) Correlation of *CPP* with the *JCSm* values for all chemistry groups. (b) Correlation of *CPP* with the *JCSm* values for all medical research groups.

We find a significant correlation between the average number of citations per publication of research groups (publication citedness, given by the indicator *CPP*) and the average journal impact of these groups (given by the journal impact indicator *JCSm*). The results are shown in Figure 9a and 9b for the entire sets of all chemistry and medical research groups, respectively. We see that the relation of *CPP* to *JCSm* is close to linear for the chemistry groups, and a slight cumulative advantage for the medical groups.

By dividing the authors into a highly cited group and a less cited group, Seglen concluded that the highly cited authors tend to publish somewhat more in journals with a higher impact than the less cited authors. Yet this difference is insufficient to explain the difference in impact between the two groups. According to Seglen, on average highly cited authors are more successful in all journal impact classes. Thus, we applied again the distinction between top- and lower-performance groups as used throughout this article in order to find performance-dominated aspects in the relation between publication citedness and journal impact level.

Following the same procedure as in Size-Dependent Cumulative Advantage of Impact, we first created within the entire set of chemistry groups two subsets on the basis of the quality judgment by peers. In one subset with 39 "top-performance" groups, these groups received the highest judgment, excellent ($Q = 5$); in another subset with 30 lower-performance groups, these groups received the lowest judgment, satisfactory ($Q = 3$). The results are given in Figure 10. We clearly notice the differences *and similarities* between the two subsets. Both the excellent as well as the

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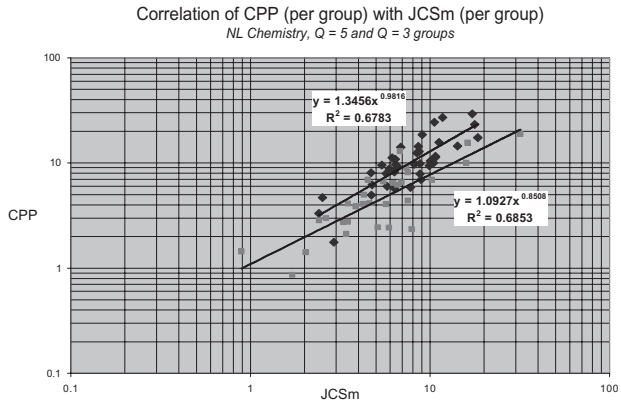

FIG. 10. Correlation of *CPP* with the *JCSm* values for the top-performance chemistry groups ($Q = 5$, indicated with diamonds), and for the lower-performance groups ($Q = 3$, indicated with squares).

TABLE 4. Power-law exponent γ of the correlation of *CPP* with *JCSm* for the two sets of groups in the indicated modalities. The differences in γ between the set of chemistry research groups and the set of medical research groups is given by $\Delta\gamma$(M, C); the difference between the top and bottom modalities (see text) by $\Delta\gamma(b, t)$. The value between parentheses has a low significance; hence no differences as indicated earlier are calculated.

	Chemistry groups	Medical groups	$\Delta\gamma$(M, C)
Top 10%	0.91	(0.59)	
Bottom 10%	0.94	1.06	*0.12*
$\Delta\gamma(b, t)$	*0.03*		
Top 20%	0.90	0.97	*0.07*
Bottom 20%	1.03	1.05	*0.02*
$\Delta\gamma(b, t)$	*0.13*	*0.08*	
Top 50%	0.90	1.17	*0.27*
Bottom 50%	0.96	1.05	*0.09*
$\Delta\gamma(b, t)$	*0.06*	*−0.12*	

satisfactory groups generally have more citations per publication (*CPP*) as a function of journal impact (*JCSm*). Clearly, the excellent groups generally have higher *CPP* values. Remarkably, the excellent as well as the satisfactory groups are more or less in the same range of journal impact values. This result nicely confirms Seglen's findings, as discussed.

Thus, our third main observation in the present study is that top-performance groups are, on average, more successful in the entire range of journal impact. In other words, they perform better in the lower-impact journals as well as in the higher-impact journals. Next, we also notice that there is no cumulative advantage: i.e., the power-law exponent of the correlation function is about (excellent groups) or below (satisfactory groups) value 1.

We now carry out the same analysis on the basis of the field-normalized impact indicator *CPP/FCSm*. We created within the entire set of chemistry and medical research groups the following subsets: groups belonging to the top 10%, 20%, and 50%, as well as to the bottom 10%, 20%, and 50% of the *CPP/FCSm* distribution. The results[12] are shown in Figure 11a and 11b (top 20% and bottom 20%, chemistry and medical groups, respectively) and 11c and 11d (top 50% and bottom 50%, chemistry and medical groups, respectively).

We observe the same phenomena for the chemistry research groups as found in Figure 10. However, the top 10% and 20% of the *CPP/FCSm* distribution have, in comparison to the groups with the peer judgment excellent, a slight preference for the higher-impact journals (Figure 11a). For the medical groups this phenomenon is even more pronounced. The top 10% and 20% (the latter in Figure 11b) of the medical groups appear to focus heavily on the high-impact journals! In the case of the chemistry groups, the ratio of the correlation coefficients provides a quantitative measure of the extent to which top groups have a higher citedness as compared to lower-performance groups. For top 10% and bottom 10% the ratio of the correlation coefficients is 3.45, for top 20% and bottom 20% it is 3.07, and for top 50% and bottom 50% we find 1.87. This finding means that the chemistry top groups perform in terms of citations per publications (*CPP*) with a factor of about 2 to 3.5 better than the bottom-groups *in the same journals*. Also this finding is in agreement with Seglen's results, which show a factor between 1.5 and 3.5.

An overview of the exponents of the correlation functions is given in Table 4.

In general, we see correlation function exponents close to 1, which indicate that the number of citations per publication is approximately a linear function of journal impact. By randomly removing 10 groups in the set of chemistry research groups and recalculating the correlation functions, we estimate that the uncertainty in the power-law exponents is about ± 0.04. Therefore, we conclude that only in the case of the medical research groups might there be a slight cumulative advantage of *CPP* with *JCSm*, particularly for the top 50%.

Finally, we analyzed the correlation between the number of not-cited publications (*Pnc*) of a group and its average journal impact level (*JCSm*). The results for the medical research groups are shown in Figure 12a. We see a quite significant correlation between these two variables. Given the strong correlation between *CPP* and *JCSm* (see Figure 9b), we can also expect a significant correlation between *Pnc* and *CPP*, as confirmed by Figure 12b. We observe that the higher the mean number of citations in a group, the lower the number of not-cited publications in a group. In other words, groups that are cited more per paper also have more cited papers. These findings underline the generally good correlation at the group level between the mean citedness of publications of a group and its mean journal impact.

Summary of the Main Findings and Concluding Remarks

We studied performance-related statistical properties of bibliometric characteristics of two sets of research groups, 157 chemistry and 65 medical research groups, covering a

[12]To prevent overloading this paper with figures, we leave out the top 10% and bottom 10% figures. These results are, however, included in Table 4.

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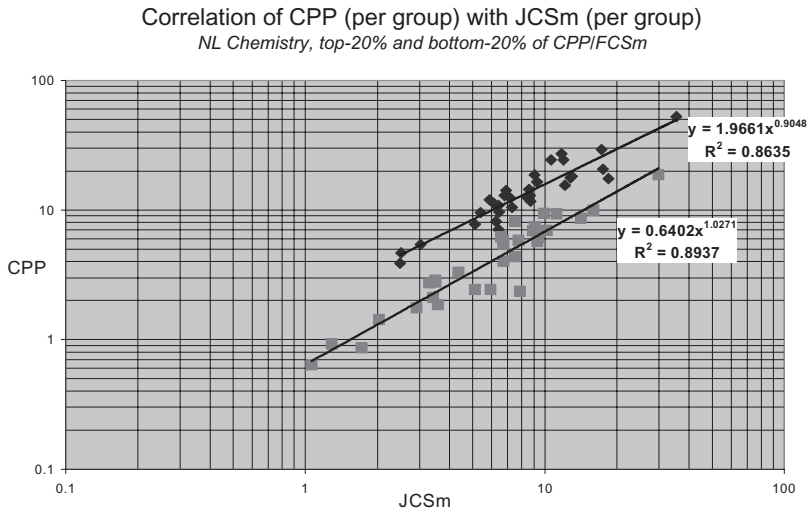

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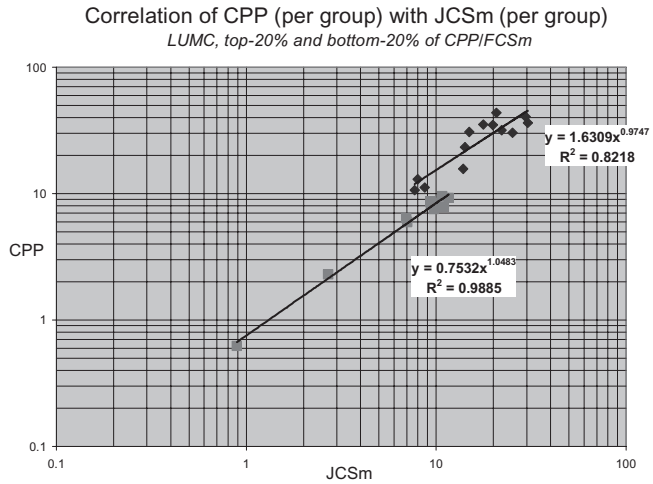

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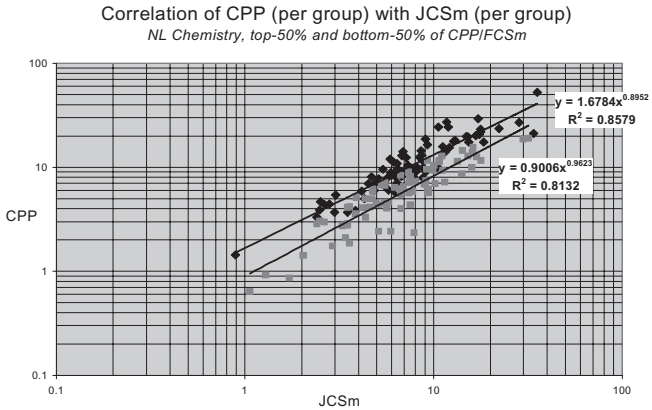

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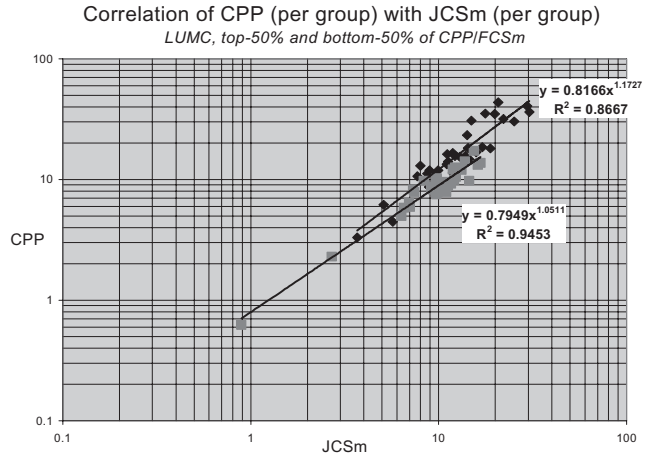

(d)

FIG. 11. (a) Correlation of the number of citations (*C*) received per chemistry research group with the number of publications (*P*), for the top 20% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 20% groups (indicated with squares). (b) Correlation of the number of citations (*C*) received per medical research group with the number of publications (*P*), for the top 20% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 20% groups (indicated with squares). (c) Correlation of the number of citations (*C*) received per chemistry research group with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 50% groups (indicated with squares). (d) Correlation of the number of citations (*C*) received per medical research group with the number of publications (*P*), for the top 50% (of *CPP/FCSm*) groups (indicated with diamonds), and for the bottom 50% groups (indicated with squares).

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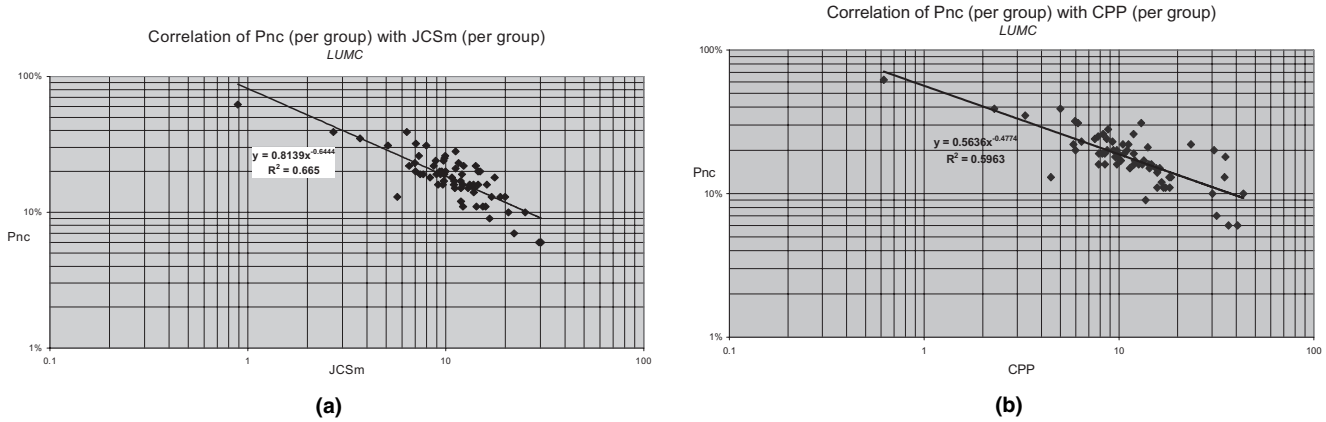

FIG. 12. (a) Correlation of the number of not-cited publications (*Pnc*) of medical research groups with the mean journal impact (*JCSm*) of a group. (b) Correlation of the number of not-cited publications (*Pnc*) of medical research groups with the mean number of citations per publication (*CPP*) of a group.

period of at least 10 years. Our main observations are as follows:

First, we find a size-dependent cumulative advantage for the total impact of research groups in terms of total number of citations. Quite remarkably, *lower-performance groups* have a *larger size-dependent cumulative advantage* for receiving citations than top-performance groups (Size-Dependent Cumulative Advantage of Impact).

Second, *regardless of performance*, larger groups have fewer not-cited publications. By distinguishing again between top- and lower-performance groups, we also discovered that particularly for the *lower-performance groups* the *fraction of not-cited publications decreases* considerably with size. We introduce in Modeling Advantages a simple model in which size is advantageous in an "internal promotion mechanism" to have more publications cited. Thus, in this model size is a distinctive parameter, which acts as a bridge between the macropicture (characteristics of the entire set of groups) and the micropicture (characteristics within a group). Therefore, the group is a crucial entity, it is not "just a set of publications" (as is more or less the case for journals). The group represents the social structure in which the promotion mechanism can work.

Given this crucial role of groups, we fit in The Concept of Hierarchically Layered Networks of Publications and Groups our findings into a concept of hierarchically layered networks. In this concept, which provides the "infrastructure" for the promotion mechanism model, the network of research groups constitutes a layer of one hierarchical step higher than the basic network of publications connected by citations. The cumulative size advantage of citations received by a group looks like preferential attachment in which highly connected nodes (publications) increase their connectivity faster than less connected nodes. But in our study of research groups it is not the number of already existing links (*C*) but the size in terms of number of papers (*P*) that causes a preference: *a size-dependent* cumulative advantage. We find that the larger a group, the more incoming links in a preferential (advantageous) nonlinear way.

We also observe that the top 10% groups are about an order of magnitude more efficient in creating linkages (*C*) than the bottom 10% groups (see Figure 3a). As our criterion concerning top or low performance is based on the field-normalized indicator *CPP/FCSm*, we hypothesize that in network terms this indicator represents the *fitness* of a group as a node in the group-network. It places a group in a better position to acquire additional links on the basis of quality (high performance). This finding implies that together with the size-dependent mechanism, preferential attachment, a quite common characteristic of complex networks, also works. Preferential attachment is based on the idea that other nodes, for instance, newcomers, feel the attractiveness (fitness) of a node and therefore also want to have a link with it.

The third main observation is a significant correlation between the average number of citations per publication (publication citedness, *CPP*) and the average journal impact of these groups (journal impact indicator *JCSm*). Top-performance groups are, on average, more successful in the entire range of journal impact, with a factor of about 2 to 3.5. In other words, top groups perform better in the lower-impact journals as well as in the higher-impact journals. There is no clear evidence of cumulative advantage for the citedness of publications with journal impact. Only in the case of the medical research groups might there be a slight cumulative advantage, particularly for the top groups.

In this study we "translate" typical bibliometric properties into network-related properties. The number of citations to a group, or total impact (*C*), is the "external wiring" of the group as a node in the network. The number of publications (*P*) is the size of the group as network node, so that *CPP* is the size-normalized impact. As discussed, the field-normalized impact (*CPP/FCSm*) represents the fitness of a group as a node in a network structure. The field-based impact *FCSm* can be seen as a general *local property* for a family of groups (in the same field) in a network that encompasses many fields of one or more larger disciplines.

How does the journal impact indicator *JCSm* fit into this picture? We think that *JCSm* can be conceived of as an

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internal characteristic, a kind of a "basic facility" to put the group in a better position. By analogy with a social context one could think of educational level (van Raan, 2006a). A higher level of education offers the potential to reach a higher income level, but this is not automatic, and with a relatively low educational level one still has a chance for a high income (in network terms: external wiring, or incoming links). In a forthcoming paper (van Raan, 2006b) we study in more detail the influence of journal impact on the cumulative advantage in the correlation between number of citations received by a group and number of publications.

In addition to the intriguing differences between top-performance and lower-performance groups, we find differences between the two sets of research groups. The chemistry groups are from 10 different universities, they have grown more or less "naturally," and they are not subject to one specific research policy strategy as all 10 universities have their own priorities. The medical groups, however, are all within one large institution. Although they also can be considered as having a "natural" basis as a research group around one or two full professors, these groups are at the same time influenced by the policy of the LUMC as a whole. Close mutual collaboration and the availability of the best people and facilities of a wide range of groups in the same location may enhance performance. Currently we are extending this study to more large sets of research groups in different scientific fields in order to investigate whether the differences found in this study between the chemical and the medical research groups are indeed due to research management–related aspects or whether discipline-related aspects play a dominant role.

Finally, further empirical work in necessary to substantiate the model of the hierarchical layered network and to position this model in terms of current models of scientific research and, particularly, citation processes.

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Appendix A: CWTS Standard Bibliometric Indicators

P	Number of publications in *CI*-covered journals of the research group in the entire period.
Ci, *C*	Number of citations received by *P* during the entire period, with and without self-citations, respectively.
CPPi, *CPP*	Average number of citations per publication, with and without self-citations, respectively.
Pnc	Percentage of publications not cited (in the given period).
JCS	Journal citation score, i.e., journal-based worldwide average impact as an international reference level for the research group, without self-citations (on a worldwide scale). In the case of more than one journal (almost always) we use the weighted average *JCSm*; for the calculation of *JCSm* the same publication and citation counting procedure, time windows, and article types are used as in the case of *CPP*.
FCS	Field citation score, i.e., field-based worldwide average impact as an international reference level for the research group, without self-citations (on a worldwide scale). In the case of more than one field (almost always) we use the weighted average *FCSm*; for the calculation of *FCSm* the same publication and citation counting procedure, time windows, and article types are used as in the case of *CPP*.
CPP/JCSm	Ratio of the actually received international impact of the research group with the worldwide average based on *JCSm* as a standard, without self-citations.
CPP/FCSm	Ratio of the actually received international impact of the research group with the worldwide average based on *FCSm* as a standard, without self-citations.
JCSm/FCSm	Journal-level indicator, e.g., to answer the question, Is the research group publishing in top or in subtop (in terms of citedness) journals?
SelfCit	Percentage of self-citations of the research group.

Appendix B: Analogy With the Cobb-Douglas Economic Production Function

The Cobb-Douglas production function in mathematical economics (Chiang, 1984) describes the economic production Q as a function of the variables capital (K) and labor (L) with the following general expression:

$$Q(K, L) = \mathrm{A}K^{\alpha}L^{\beta}, A \text{ is a constant, } \alpha \text{ and } \beta \text{ are exponential parameters.}$$

In the case that economic production is primarily dependent only on one variable, say, labor, which means that we take capital as a constant ($\alpha = 1$), so that $Q(L) = AL^{\beta}$.

In the case of $\beta > 1$, economists speak about "increasing returns to scale" (in terms of labor), and for $\beta < 1$ we have decreasing returns to scale.

This is comparable to our "citation production function," in general form: $C(P) = aP^{\gamma}$ (with a as a constant, and γ the exponential parameter).

By analogy with economic production, we may say that impact (C) is produced by "scientific labor" (publications, P), and in the case of $\gamma > 1$ we have increasing "returns to scale," or a cumulative advantage by size.

An interesting extension of this analogy is the following: The derivative of the economic production function Q with labor L, the differential quotient dQ/dL (the "marginal function" in economic terms), divided by the "average function" Q/L is the economic *elasticity*. In the preceding case with one variable, we have

$$(dQ/dL)/(Q/L) = (A\beta L^{\beta-1})/AL^{\beta-1} = \beta.$$

In this analogy, the power-law exponent γ in the correlation between citations and publications, $C(P) = aP^{\gamma}$, can be seen as "bibliometric elasticity":

$$(dC/dP)/(C/P) = (a\gamma P^{\gamma-1})/(aP^{\gamma-1}) = \gamma.$$

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