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SCIENCE DYNAMICS: NORMALIZED GROWTH CURVES, SHARPE RATIOS, AND SCALING EXPONENTS

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Abstract
Many indicators exist that measure different aspects of scientific productivity, impact, and collaboration. Longitudinal analyses are commonly used to identify developments and changes. However, indicators to quantify dynamics are largely missing and scholarly articles documenting the use of a dynamics indicator are rare. This paper aims at contributing to their development and application. Using *Scopus*, time series of four output indicators in 13 years are observed for 27 disciplines. One qualitative way and two quantitative ways to study dynamics are discussed. The qualitative way is to visualize the data. The first quantitative method to measure growth, the Sharpe Ratio, is imported from portfolio management. The second method is the application of scaling analysis, a way to describe how two properties of a system, like authors and publications, relate to each other as the system undergoes size changes in time. We show that the database is a source of artificial growth, confirming earlier results. Visualizations are an important step to get to know the data, identify potential problems, and generally help interpret quantitative results. The two dynamics indicators reveal different perspectives of growth, but results are correlated with a Pearson coefficient of at least 0.67.

Conference Topic
Scientometrics Indicators - Criticism and new developments (Topic 1), Old and New Data Sources for Scientometric Studies: Coverage, Accuracy and Reliability (Topic 2), and Science Policy and Research Evaluation: Quantitative and Qualitative Approaches (Topic 3).

Introduction
At the same time that the science system experiences growth, globalization, and an increase of interdisciplinary, team, and project work, scientometrics are becoming effectively available. To keep track of developments and analyze its actions, science policy is increasingly interested in scientometric analyses. Many

indicators have been developed and continue to be developed that quantify different aspects of scientific productivity, impact, and collaboration. Longitudinal analyses are commonly used to identify developments and changes. However, indicators to measure dynamics are largely missing. Scholarly articles documenting the use of a dynamics indicator are rare (Grupp *et al.*, 2009). This paper aims at contributing to their development and application.

Using *Scopus*, time series of four output indicators in 13 years are observed for 27 disciplines. One qualitative way and two quantitative ways to study dynamics are discussed. The qualitative way is to visualize the data. Normalizations can be applied to enable comparisons. The first method to quantify growth, the Sharpe Ratio, is imported from portfolio management (Sharpe, 1994). There, it is important to monitor stocks in a portfolio against changes in the whole stock market—a task not so different from science evaluation where database growth must be taken into account. The second method is the application of scaling analysis (Katz, 2000; Lane *et al.*, 2009). The goal is to describe how two properties of a system, like authors and publications, relate to each other as the system undergoes size changes in time. We proceed like Bettencourt *et al.* who applied scaling analysis to measure the dynamics of publications per author (2008).

We start by describing the data and indicators in use. Visualizations are presented as an important step to get to know the data, identify potential problems, and generally help interpret quantitative results. Characteristics, applications, and limitations of the quantitative methods are discussed.

Data and Indicators

We are studying 27 scientific disciplines using the *Scopus* custom database of the German Competence Centre for Bibliometrics. Disciplines are delineated through the *All Science Journal Classification* (ASJC) provided by *Scopus*. The analysis is restricted to the document type "article" and the source type "journal." Publication years 1996 to 2008 are subject to analysis, resulting in 13 years. To avoid the problem of author deflation through homonyms (Strotmann and Zhao, 2012), the author identifier delivered by *Scopus* was used. While this identifier is not sufficiently accurate if authors are the objects of study we deem it accurate enough for macro studies such as ours. We are using disciplines as objects but the instruments to be discussed are applicable to other objects such as fields, countries, or organizations as well.

Indicators are the

- number of publications (P),
- cumulative number of authors (A_{cum}),
- authors per publication (APP), and
- publications per author (PPA).

P and A_{cum} are two measures for the size of a discipline. The assumption behind counting authors cumulatively is that scientists stay in the discipline once they have entered it. APP are calculated on the basis of items, *i.e.*, the number of distinct author identifiers A per paper P are averaged. PPA is the indicator for productivity. It is the quotient of distinct author identifiers and distinct publications.[151]

Visualizing Growth

The first possibility to study growth is to visualize the data. Figure 1 depicts P and A_{cum} growth curves of seven selected disciplines and total database content. On the level of disciplines, smooth exponential or sigmoid growth is expected (Bettencourt *et al.*, 2008). Instead, in terms of P, we are seeing jumps and dents. The Arts and Humanities jump from 4,000-5,000 publications in 1996-2001 to 7,000-8,000 in 2002-2006. This is because in 2009 the database producer included many new journals that went back as far as 2002.[152] Neuroscience is the only discipline with a publication increase in every year. Almost all disciplines show a decrease of P around the years 2002-2003. The dent is strongly pronounced in the Social Sciences and is clearly visible for the total. This can be explained historically, and reflects the different phases in the creation of *Scopus*.[153]

In general, this fact will need to be dealt with if *Scopus* and the selection of publications through the ASJC are used to measure dynamics. For the purpose of this paper, this complication is instructive. At this point it is clear that database content is a biased estimator of scientific growth.

For the purpose of comparisons it is desirable to show multiple curves in one figure. In practice it is hardly possible to combine more than ten curves without losing comprehensiveness. In addition, it is problematic to combine curves which reside at different scales because the inclusion of curves at a large scale tends to disguise details of curves at small scale. Logarithmic ordinates enable such a combination but also compress the curves and hide details.

Figure 2 (top row) combines growth curves for seven disciplines. Details are already much less visible than in the individual curves of Figure 1. Normalizing growth reintroduces detail (bottom row). To do so, all year values are divided by the initial (1996) value. It is now more easily visible that, in terms of the number of publications, Computer Science, Energy, also the Social Sciences, and Engineering grow stronger in the more recent years than the total which is shown as a solid black line.

To look at productivity (PPA) we must first look at collaboration (APP). Teams are increasingly important in the production of knowledge, most strongly in Science & Engineering, but also in the Social Sciences and the Arts & Humanities (Wuchty *et al.*, 2007). In principle, APP and PPA can grow simultaneously. Consider a field with one publication (having authors X and Y) in one year and

[151] The quotient of maximum author position and distinct publications gives similar results.
[152] Private message from the database producer Elsevier, 14 January 2013.
[153] Document and source types grow differently in Scopus. Elsevier recommends including reviews and conference proceedings articles to arrive at persistent positive growth at the discipline level. Private message from Elsevier, 17 January 2013.

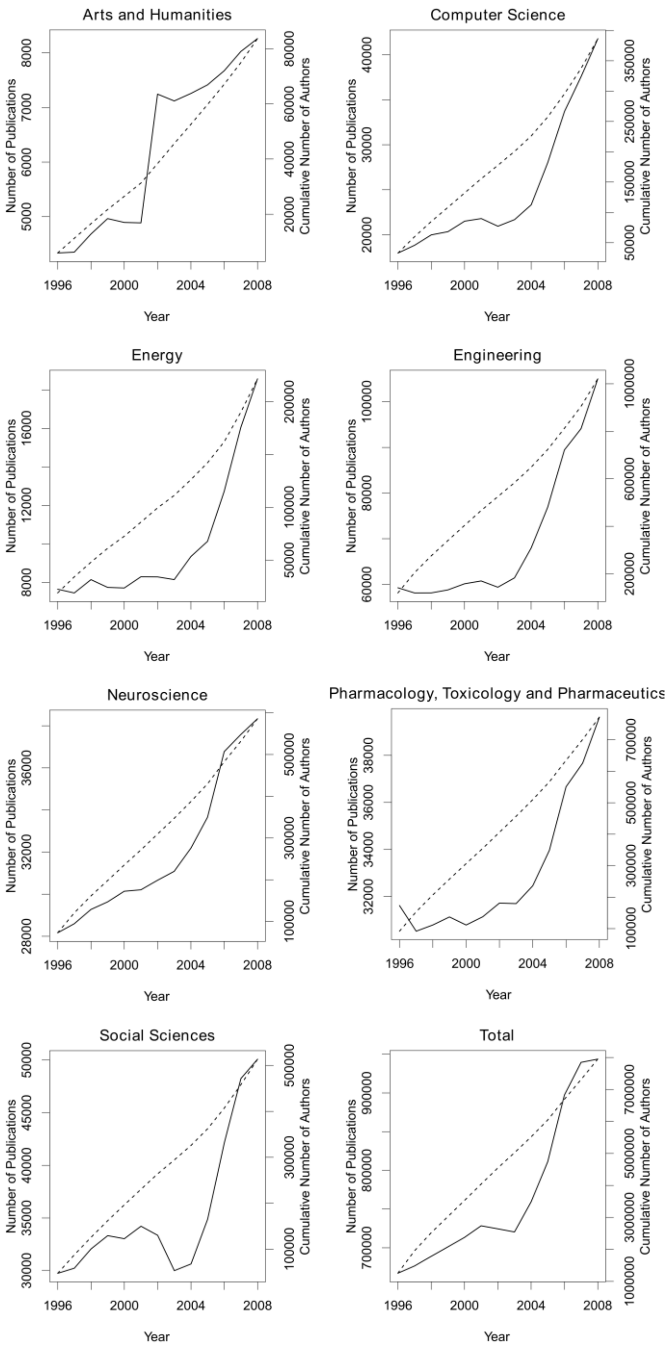

Figure 1. Growth of the number of publications (continuous lines) and the cumulative number of authors (dotted lines) for seven disciplines and total database content in separate figures.

two publications (the first having authors X and Y, the second having authors X, Y, and Z) in the following year. APP increases from 2 to 2.5, PPA increases from 1/2 to 2/3. Instead, Figure 2 shows that APP and PPA are inversely proportional when all 13 years are looked at. The increasing dominance of teams prevents a growth of productivity.

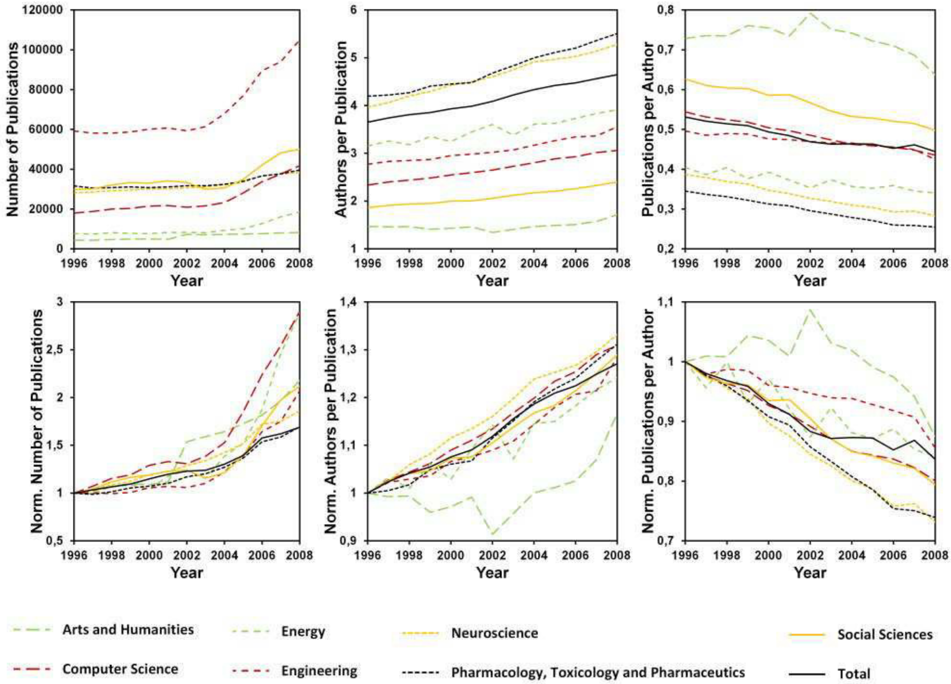

Figure 2. Growth and normalized growth curves of the number of publications, number of authors per publication, and publications per author for seven disciplines and total database content.

Table 1. Sharpe Ratios of the four indicators and scaling exponents of productivity for the whole timespan and the last five years (ranks in brackets).

Discipline	*S(P)*		*S(A_{cum})*		*S(APP)*		*S(PPA)*		*β*	
	13yrs	*5yrs*	*13yrs*	*5yrs*	*13yrs*	*5yrs*	*13yrs*	*5yrs*	*13yrs*	*5yrs*
General	-0.10 (20)	-0.48 (22)	0.84 (18)	2.58 (19)	0.25 (13)	0.20 (20)	-0.37 (14)	-0.35 (10)	0.43 (27)	0.52 (26)
Agricultural and Biological Sciences	0.33 (11)	1.58 (9)	0.96 (12)	4.08 (9)	1.51 (1)	4.16 (1)	-0.76 (22)	-0.73 (15)	0.61 (18)	0.78 (17)
Arts and Humanities	0.22 (15)	-0.62 (24)	1.03 (11)	3.23 (12)	-0.16 (22)	0.71 (11)	0.10 (3)	-1.26 (20)	0.91 (1)	0.48 (27)
Biochemistry, Genetics and Molecular	-0.20 (22)	-0.40 (21)	0.92 (14)	9.46 (3)	0.69 (7)	0.43 (16)	-1.63 (27)	-1.53 (23)	0.55 (22)	0.69 (19)

Biology										
Business, Management and Accounting	0.36 (9)	1.41 (12)	0.88 (16)	11.48 (2)	-0.28 (24)	-2.18 (27)	0.06 (4)	0.95 (1)	0.87 (2)	1.09 (1)
Chemical Engineering	0.64 (2)	0.98 (14)	1.28 (1)	2.58 (18)	0.42 (11)	1.46 (4)	-0.40 (17)	-0.90 (17)	0.77 (8)	0.81 (14)
Chemistry	0.21 (16)	0.31 (18)	1.24 (3)	1.34 (25)	-0.16 (21)	0.96 (9)	-0.07 (9)	-0.44 (12)	0.71 (14)	0.79 (16)
Computer Science	0.96 (1)	4.25 (2)	1.04 (10)	7.42 (5)	0.54 (10)	0.97 (8)	-0.26 (11)	-0.22 (7)	0.81 (7)	0.91 (6)
Decision Sciences	0.34 (10)	2.94 (4)	0.75 (22)	1.83 (22)	-0.46 (27)	-0.05 (23)	0.02 (6)	0.02 (4)	0.82 (6)	0.95 (3)
Dentistry	0.32 (12)	0.47 (16)	1.27 (2)	5.12 (7)	0.72 (6)	0.59 (13)	-0.76 (23)	-1.06 (19)	0.57 (21)	0.76 (18)
Earth and Planetary Sciences	-0.15 (21)	-0.76 (27)	0.38 (26)	0.41 (27)	1.14 (2)	1.13 (5)	-0.38 (15)	-0.51 (13)	0.63 (17)	0.69 (21)
Economics, Econometrics and Finance	0.45 (7)	1.89 (7)	0.75 (21)	2.36 (20)	-0.40 (25)	0.32 (18)	-0.11 (10)	-0.25 (8)	0.76 (9)	0.89 (9)
Energy	0.62 (3)	1.84 (8)	1.08 (6)	2.31 (21)	-0.03 (19)	0.27 (19)	0.03 (5)	-0.02 (5)	0.87 (3)	0.94 (4)
Engineering	0.50 (4)	1.57 (10)	0.82 (19)	2.59 (17)	0.06 (17)	0.64 (12)	0.12 (2)	-0.78 (16)	0.84 (5)	0.84 (12)
Environmental Science	0.10 (17)	1.46 (11)	0.70 (24)	7.46 (4)	0.88 (4)	3.84 (2)	-0.62 (19)	-1.27 (21)	0.72 (12)	0.84 (13)
Health Professions	-0.27 (25)	-0.65 (25)	0.91 (15)	2.93 (14)	-0.41 (26)	-1.49 (26)	-0.38 (16)	-1.60 (24)	0.57 (20)	0.80 (15)
Immunology and Microbiology	-0.30 (26)	-0.53 (23)	0.94 (13)	3.93 (10)	0.59 (9)	0.54 (14)	-1.44 (26)	-1.82 (26)	0.48 (25)	0.66 (25)
Materials Science	0.46 (6)	1.15 (13)	0.70 (23)	1.53 (24)	-0.06 (20)	0.99 (7)	0.21 (1)	-0.15 (6)	0.85 (4)	0.90 (7)
Mathematics	0.42 (8)	2.73 (6)	0.69 (25)	1.62 (23)	0.24 (14)	0.32 (17)	-0.56 (18)	-1.30 (22)	0.61 (19)	0.68 (23)
Medicine	0.30 (14)	3.32 (3)	1.07 (7)	3.08 (13)	0.18 (15)	-0.15 (24)	-0.36 (13)	0.18 (3)	0.66 (16)	0.92 (5)
Neuroscience	-0.22 (24)	-0.71 (26)	1.07 (8)	6.05 (6)	0.60 (8)	0.13 (22)	-1.36 (25)	-2.56 (27)	0.51 (23)	0.69 (20)
Nursing	0.49 (5)	10.61 (1)	1.08 (5)	2.73 (16)	0.83 (5)	0.52 (15)	-0.73 (21)	-0.91 (18)	0.68 (15)	0.89 (10)
Pharmacology, Toxicology and Pharmaceutics	-0.42 (27)	-0.17 (20)	1.06 (9)	12.98 (1)	0.25 (12)	2.50 (3)	-0.72 (20)	-0.61 (14)	0.47 (26)	0.69 (22)
Physics and Astronomy	-0.07 (19)	0.46 (17)	-0.71 (27)	0.49 (26)	-0.24 (23)	0.19 (21)	-0.03 (7)	-0.27 (9)	0.75 (10)	0.85 (11)
Psychology	0.08 (18)	0.84 (15)	0.86 (17)	3.37 (11)	0.06 (18)	-0.40 (25)	-0.03 (8)	0.38 (2)	0.71 (13)	1.03 (2)
Social Sciences	0.32 (13)	2.77 (5)	0.78 (20)	2.92 (15)	0.17 (16)	0.95 (10)	-0.29 (12)	-0.43 (11)	0.74 (11)	0.90 (8)
Veterinary	-0.20 (23)	-0.17 (19)	1.11 (4)	4.73 (8)	0.94 (3)	1.07 (6)	-0.83 (24)	-1.63 (25)	0.48 (24)	0.67 (24)
Total	—	—	—	—	—	—	—	—	0.71	0.88

While figures of normalized variables obscure dimensions, they are capable of delivering basic growth messages in a qualitative way. When quantifying growth two things should be kept in mind. First, because database content is itself dynamic indicators should correct for that. Second, due to changes in growth it may be necessary to compute growth indicators for different time regimes. In our case, because of the dynamics of the *Scopus* database itself, we will study indicators for all 13 years and just the last five years where dynamics are more stable.

The Sharpe Ratio

The Sharpe Ratio is a metric from financial portfolio management, a measure of average annual growth (Sharpe, 1994). It has been applied in science policy contexts to identify key institutions (Schmoch *et al.*, 2006) and dynamic research fields (Grupp *et al.*, 2009). Although in these and other studies the metric is applied to raw publication counts, in principle it can be applied to describe the dynamics of all indicators. The (historic) Sharpe Ratio of a quantity N_i in discipline i is defined as

$$S(N_i) = \frac{\overline{D_\iota(t)}}{\sigma_{D_i(t)}} \tag{1}$$

with

$$D_i(t) = \frac{N_i(t+1) - N_i(t)}{N_i(t)} - \frac{N_{total}(t+1) - N_{total}(t)}{N_{total}(t)} \tag{2}$$

where $\overline{D_\iota(t)}$ is the average of $D_i(t)$ and $\sigma_{D_i(t)}$ is its standard deviation. In words, first, the annual growth rate of the desired quantity in discipline i is calculated for each year. Second, to normalize for database growth the annual growth rate of the total is subtracted, giving the normalized annual growth rate. Third, the normalized annual growth rate is averaged over all years, giving the average normalized growth rate. Fourth, the average normalized growth rate is divided by the standard deviation of the normalized annual growth rates. Since the standard deviation is small when the normalized annual growth rates do not vary much, steady growth is rewarded and erratic growth is punished.

Table 1 gives the Sharpe Ratios for all 13 years and just the last five years. S is not intuitively interpretable. A negative value does not imply negative growth, it means that a discipline grows less than the total. The indicator confirms the impressions from Figure 2. Computer Science, Energy, and Engineering have the strongest publication growth. Pharmacology, Toxicology and Pharmaceutics has a negative Sharpe Ratio and occupies the last rank position. Because the Arts and Humanities hardly grow except for the artificial jump, they take almost last rank when just the last five years are considered. The top rank for Nursing is because the number of publications more than doubled in the last five years which again is an artifact of database production.

Regarding productivity, the three top curves of Figure 2, Engineering (0.12), Arts and Humanities (0.10), and Energy (0.03) are among the disciplines with the highest Sharpe Ratios. Pharmacology, Toxicology and Pharmaceutics (-0.72) as well as Neuroscience (-1.36) grow much less than the total, as can be seen in the figure. When just the last five years are considered, the Arts and Humanities fall 17 rank positions, reflecting that the artifact does not influence the score anymore. It may be surprising that only six scientific disciplines exhibit a growth of productivity. Again, we look at its relation to cooperation, now in a quantitative way. Engineering is the only discipline with both cooperation and productivity growth. The average growth of cooperation in all 27 disciplines over 13 years is 0.29 while average productivity growth is -0.43. The Pearson correlation coefficient of both quantities is -0.64. This confirms the impression from Figure 2 that, overall, the increasing dominance of teams indeed prevents a growth of productivity. And teams do become more important. Cooperation growth is even bigger (0.69) when just the last five years are studied. Recent 5 year average cooperation growth is 137% bigger than overall 13 year growth. Productivity, on the other hand, does not decrease as drastically. Recent 5 year average productivity growth (-0.71) is just 65% bigger than 13 year growth. In the 5 year window, correlation of both quantities gets lost (the Pearson coefficient is -0.24). This may indicate that science is entering a phase where productivity grows despite growing cooperation, but confidence in this statement is muddled due to the database artifact we have found.

Scaling Analysis

Another way to quantify dynamics is scaling analysis, a method to study the behaviour of a complex system across spatial or temporal scales (Lane *et al.*, 2009). Scaling analysis belongs to modeling but can also be used for evaluation purposes. A system is said to scale when two properties N and Y are related through a power law $Y \propto N^{\alpha}$. The scaling exponent α is then a system-specific descriptor of the average relative change in Y with N. If $\alpha > 1$, Y/N increases with N (increasing returns). On the contrary, if $\alpha < 1$, Y/N decreases in an economy of scale. For $\alpha = 1$, Y/N is constant.

Originating in biology, astrophysics, and urban studies, scaling analysis was later applied to science and innovation systems and it was demonstrated that different scientific disciplines all share the property of scale invariance, making the method applicable to systems with different publication behaviors (Katz, 1999, 2000). Bettencourt *et al.* (2008) have applied scaling analysis to model science system dynamics. If N is the number of authors A at time t and Y is the number of publications P at that time, $\beta > 1$ ($\beta < 1$) characterizes a research field with increasing (decreasing) individual productivity (PPA):

$$P_i(t) \propto A_i(t)^{\beta} \tag{3}$$

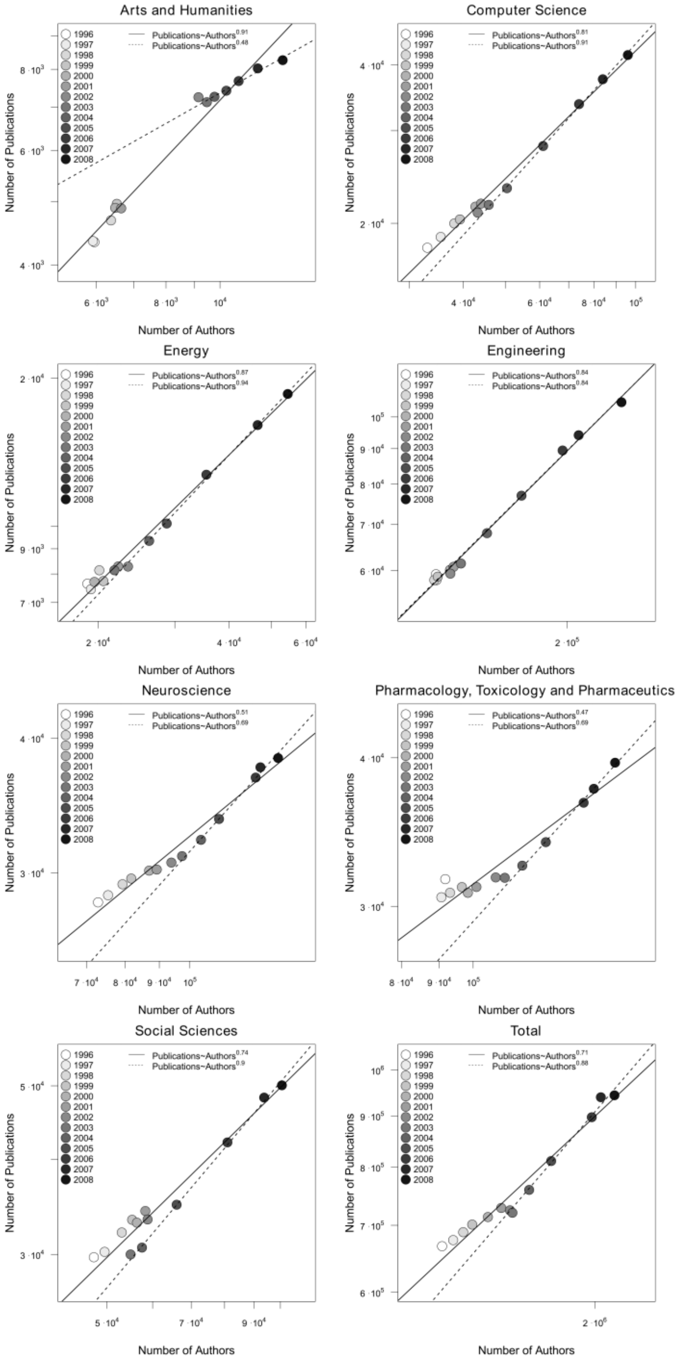

Figure 3. Scaling analysis (productivity) of seven disciplines and total database content (the continuous line is a fit to all data points, the dotted line to just the last 5 years).

We have used standardized major axis analysis, implemented in R, to estimate the scaling exponent β because the method is scale invariant and we are not interested in inference (Warton *et al.*, 2006, 2012).
Results are given in Figure 3 and Table 1. Each data point in a figure corresponds to a year. Grayscales are used to mark years. If both A and P increase monotonously from year to year data points monotonously move from the bottom left to the upper right corner as time passes. This is only the case for Neuroscience. But even there different growth regimes are visible as non-parallel lines. Continuous lines are fits to all 13 years, dotted lines just to the last five years. The artifact caused by database growth is visible in most disciplines, also for the total database content. In the Social Sciences the second regime starts at a scale way below of what had been reached in the first regime. In the Arts and Humanities it is now clearly visible that in the last five years growth is much smaller than for the system as a whole.
Exponents for all disciplines are smaller than 1, saying that productivity decreases as size increases. Top disciplines are those with largest exponents. Again, the Arts and Humanities (0.90), Energy (0.87), and Engineering (0.84) have top scores while Pharmacology, Toxicology and Pharmaceutics (0.47) and Neuroscience (0.51) are at the lower end of productivity. When just considering the last five years, the Arts and Humanities are punished more than if the Sharpe Ratio is used. They drop from first to last rank position.
Even though β and S are different perspectives on growth, the two indicators are quite strongly correlated. Pearson correlation coefficients are 0.77 for the whole timespan and 0.67 for the last five years. This is because β is mathematically related to changes in Y/N, the annual growth rate, that S is based on.

Discussion and Conclusion

Starting from a need for metrics of dynamics in the science system, visual growth curves, the Sharpe Ratio, and scaling exponents were discussed. Curves can unveil essential meanings in a qualitative way. Comparison of objects of study is made easier by normalizing curves. In our case, the visualization revealed different growth regimes where just one regime was expected, showing that the database is a source of artificial growth, confirming earlier results (Larsen and Ins, 2010; Michels and Schmoch, 2012). Knowing the data is thus imperative and actually looking at it should be a first step before growth is quantified.
Two metrics, the Sharpe Ratio S and scaling exponent β, were discussed and applied to whole and partial timespans to cope with the presence of different growth regimes. The Sharpe Ratio is based on the average annual growth rate and aims to remove artifacts by subtracting overall database growth. On the level of this study, this subtraction may be criticized because overall database content is dominated by the hard sciences but is also used to normalize the soft sciences. But once objects in a coherent field are studied, like countries in a discipline, such a normalization immediately makes sense. In addition, the Sharpe Ratio addresses

the stability of growth by dividing by the standard deviation of the normalized annual growth rates.

In scaling analysis, visualizations also proved to be important as they made different regimes very transparent and stressed the need to fit different functions to them (Bettencourt *et al.*, 2008). A spontaneous reaction is to criticize fits to just five data points. Of course, the fewer data points there are, the more each one influences the result. But this is also true for the average growth rate which is frequently used also for small numbers. Scaling exponents are not normalized for database dynamics, but a way to normalize would be to divide by the exponent of the total.

The Sharpe Ratio can be applied to all possible time series, not just to publication counts, as common in the literature. If one does not feel comfortable with dividing by the standard deviation, this can easily be left out. Scaling analysis is only applicable to bivariate data. Besides productivity another natural application is to quantify impact dynamics (Katz, 2000).

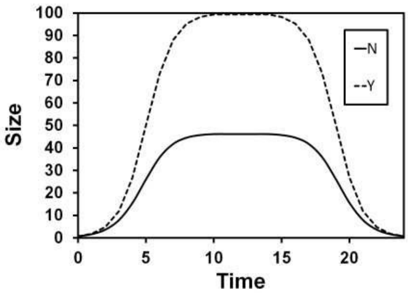

Figure 4. Growth dynamics of an hypothetical system with $Y \propto N^{1.2}$.

Scale only corresponds to time if annual growth rates are constantly positive. In other words, time does not move backwards when variables decrease. Consider the system depicted in Figure 4. It has the typical dynamics of an emerging, then persisting, and finally dying field with $Y \propto N^{1.2}$. If all years are subject to scaling analysis, the exponent will still be 1.2. If scaling analysis is done like it is done here, the only sign that the field is actually shrinking is that the data points become darker as they move from the upper right corner to the lower left. Most obvious applications of scaling analysis may be the identification and characterization of emerging science (Guo *et al.*, 2011).

To conclude, the Sharpe Ratio and scaling exponents are different perspectives on growth with different areas of applicability. They should be used in combination with growth visualizations which help get a feeling for the data and which can reveal intricacies of the system under study. A result of this technical discussion that requires further scrutiny is that the increasing dominance of teams in the production of knowledge actually prevents a growth of productivity, less so in the last five than in the last 13 years.

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References

Bettencourt, L.M.A., Kaiser, D.I., Kaur, J., Castillo-Chávez, C. & Wojick, D.E. (2008). Population modeling of the emergence and development of scientific fields. *Scientometrics*, 75, 495-518.

Grupp, H., Hinze, S., Breitschopf, B. (2009). Defining regional research priorities: a new approach. *Science and Public Policy*, 36, 549-559.

Guo, H., Weingart, S. & Börner, K. (2011). Mixed-indicators model for identifying emerging research areas. *Scientometrics*, 89, 421-435.

Katz, J.S. (1999). The self-similar science system. *Research Policy*, 28, 501-517.

Katz, J.S. (2000). Scale-independent indicators and research evaluation. *Science and Public Policy*, 27, 23-36.

Lane, D., Pumain, D. & Leeuw, S. van der (Eds.) (2009). *Complexity Perspectives in Innovation and Social Change*. Dordrecht: Springer.

Larsen, P.O. & Ins, M. von (2010). The rate of growth in scientific publication and the decline in coverage provided by Science Citation Index. *Scientometrics*, 84, 575-603.

Michels, C. & Schmoch, U. (2012). The growth of science and database coverage. *Scientometrics*, 93, 831-846.

Schmoch, U., Wang, J. & Stoica, R. (2006). *Research and Development in the Turkish Landscape of Science: Identification of Key Institutions*. Report to the Federal Ministry of Education and Research (BMBF), Fraunhofer Institute for Systems and Innovation Research.

Sharpe, W.F. (1994). The Sharpe Ratio. *The Journal of Portfolio Management*, 21, 49-58.

Strotmann, A. & Zhao, D. (2012). Author name disambiguation: What difference does it make in author-based citation analysis? *Journal of the American Society for Information Science and Technology*, 63, 1820-1833.

Warton, D.I., Duursma, R.A., Falster, D.S. & Taskinen, S. (2012). smatr 3- an R package for estimation and inference about allometric lines. *Methods in Ecology and Evolution*, 3, 257-259.

Warton, D.I., Wright, I.J., Falster, D.S. & Westoby, M. (2006). Bivariate line-fitting methods for allometry. *Biological Reviews*, 81, 259-291.

Wuchty, S., Jones, B.F. & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316, 1036-1039.