# Calculating the excellence shift: How efficiently do institutions produce highly cited papers?

Bornmann, Lutz and Wohlrabe, Klaus

12 May 2017

# Calculating the excellence shift:

# How efficiently do institutions produce highly cited papers?

Lutz Bornmann* & Klaus Wohlrabe**

*Corresponding author:

Division for Science and Innovation Studies

Administrative Headquarters of the Max Planck Society

Hofgartenstr. 8

80539 Munich, Germany

E-mail: bornmann@gv.mpg.de

**Ifo Institute

Poschingerstr. 5

81679 Munich, Germany

E-mail: Wohlrabe@ifo.de

**Abstract**

The excellence shift is proposed, which shows universities' ability to produce highly cited papers as measured against their basic academic research efficiency (ARE). To demonstrate our approach, we use data from 50 US universities.

JEL Codes

I21, I23, A12

**Key words**

Efficiency, high-impact papers, excellence shift

# Introduction

Questions of academic research efficiency (ARE) have gained increasing interest in recent years. One important reason may be the advance of new public management in the science system (Bornmann, 2017). According to Rhaiem (2017), the literature on ARE has grown exponentially in the past few years. The *Journal of Informetrics* recently published the discussion of an opinion paper by Abramo and D'Angelo (2016), who argued for a switch to the use of ARE instead of the mean normalized citation score (MNCS, Waltman, van Eck, van Leeuwen, Visser, & van Raan, 2011) and other size-independent indicators (e.g., percentiles, see Bornmann, Leydesdorff, & Mutz, 2013) in research evaluation. Whereas size-independent indicators focus on the mean citation impact, indicators of ARE relate output data (e.g., number of highly cited papers) to input data (e.g., number of researchers or expenses).

In their comment on the opinion paper, Bornmann and Haunschild (2016) argue against this switch in the current practice of research evaluation, explaining that more research is needed on measuring ARE. In this paper, we propose a simple method of measuring ARE. Our approach solves a common problem in measuring efficiency and productivity in science: the lack of comparability of academic institutions. For example, one university might be more focused on teaching than on research and vice versa. Furthermore, the disciplinary profiles of universities are different. So in many cases, especially with large data sets, it is difficult to clearly identify comparable input and output measures across entities. This measurement problem is a serious issue with respect to this research area of academic efficiency measurement (see Wohlrabe, de Moya Anegon, & Bornmann, 2017, for more details and references).

We illustrate our approach using input and output data for 50 US universities.

# Data and methods

In order to demonstrate our approach, we use data for the 50 best-performing US universities as listed in the Times Higher Education World University (THE) Ranking 2015 (see www.timeshighereducation.com). The input indicator is the universities' total budget. The data source is the National Center for Education Statistics (NCES).[1] Further details on the input data can be found in Wohlrabe et al. (2017). On the output side, our approach is based on two indicators: (1) the total number of citable publications (P) and (2) the total number of publications belonging to the 10% most frequently cited publications in their subject area and publication year ($P_{top\ 10\%}$). The bibliometric data are from the SCImago Institutions Rankings (see www.scimagoir.com), which contain reliable publication data at the institutional level. Table 1 shows the data for 2013. Harvard University, for example, published 19,805 papers in 2013, with 4,805 papers belonging to $P_{top\ 10\%}$. Its budget was $ 4.16 bn.

Given our dataset, the excellence shift is formally calculated as follows:

1. The relative shares $p_{1i}=P_i/\Sigma P_i$; $p_{2i}=P_{top\ 10\%,\ i}/\Sigma P_{top\ 10\%,\ i}$ and $b_i=Budget_i/\Sigma Budget_i$ are calculated. These represent the share of each university given the sum of inputs and outputs, respectively. The percentages standardize the absolute numbers and make them comparable across indicators.
2. The university efficiency scores for the two outputs given by $e_1=p_{1i}/b_i$ and $e_2=p_{2i}/b_i$ are calculated. These are simple productivity measures relating the outputs to the inputs.
3. The excellence shift is the difference between the two efficiency scores $e_2$-$e_1$.

# Results

Following these formulas, we summarise P, $P_{top\ 10\%}$ and budget across the 50 universities (see Table 1). For example, the calculations for Harvard University yield 3.03%

[1] The data can be downloaded from http://nces.ed.gov/ipeds/datacenter/InstitutionProfile.aspx?unitid=adafaeb2afaf

of total available budget and 6.69% of all publications. The comparison of percentages shows that Harvard University produces more papers than could be expected from the available budget. On the output side, two percentages are calculated across the universities: for P and $P_{top\ 10\%}$. The second step of the approach results in two ratios, demonstrating the gain or loss in output when the budget percentages are related to the publication percentages: budget/P and budget/$P_{top\ 10\%}$. In the third step, the former is subtracted from the latter, which yields the excellence shift.

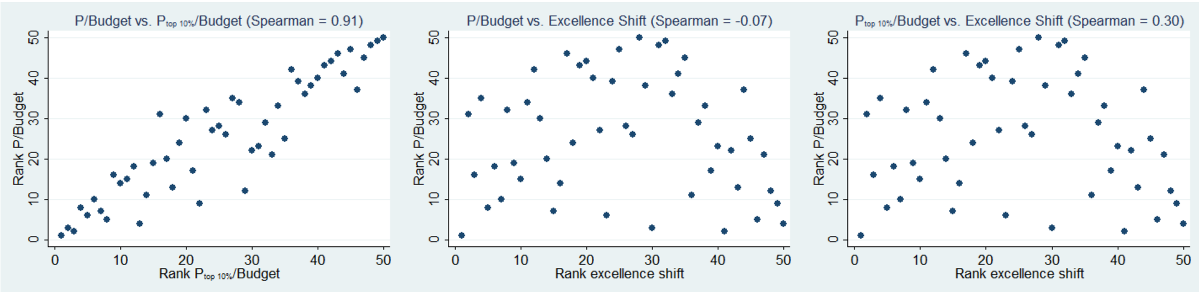
The excellence shift in Table 1 shows whether a university is able to produce high-level research when compared with its own basic efficiency score – as measured by the budget/P ratio. Thus, comparing the 50 universities in Table 1 reveals which universities are able to gain more than the others from their basic efficiency in producing high-level research. This approach solves an important problem in efficiency studies: the universities are so different in their missions, disciplinary profiles and sizes that they are actually not comparable. Comparing each university with its own basic efficiency obviates the need to standardize it (in terms of size, disciplinary profile and mission). With a positive excellence shift of 0.43, Harvard University produces more top-level research than any other university in the table as compared with their own possibilities. The Georgia Institute of Technology shows the highest negative excellence shift, with a value of -0.46. With respect to its own basic efficiency score, this university is below its potential for conducting top-level research.

Table 1. Input and output indicators for 50 universities and the resulting excellence shift (decreasing sorted by the excellence shift)

| University | Budget (in $bn) | % Budget | P | $P_{top\ 10\%}$ | % P | % $P_{top\ 10\%}$ | P/ Budget | $P_{top\ 10\%}$/ Budget | Excellence shift |
|---|---|---|---|---|---|---|---|---|---|
| Harvard University | 4.16 | 3.03 | 19805 | 4805 | 6.69 | 8.01 | 2.21 | 2.64 | 0.43 |
| Stanford University | 4.16 | 3.03 | 9222 | 2356 | 3.12 | 3.93 | 1.03 | 1.30 | 0.27 |
| Massachusetts Institute of Technology | 2.91 | 2.12 | 7998 | 1901 | 2.70 | 3.17 | 1.27 | 1.49 | 0.22 |
| University of California, San Diego | 3.73 | 2.72 | 6847 | 1693 | 2.31 | 2.82 | 0.85 | 1.04 | 0.19 |
| University of California, Santa Barbara | 0.91 | 0.66 | 2970 | 674 | 1.00 | 1.12 | 1.51 | 1.69 | 0.18 |
| University of California, Santa Cruz | 0.64 | 0.47 | 1696 | 389 | 0.57 | 0.65 | 1.23 | 1.39 | 0.16 |
| Rice University | 0.58 | 0.43 | 1827 | 409 | 0.62 | 0.68 | 1.45 | 1.60 | 0.15 |
| California Institute of Technology | 2.11 | 1.54 | 4462 | 1015 | 1.51 | 1.69 | 0.98 | 1.10 | 0.12 |
| Princeton University | 1.44 | 1.05 | 3805 | 839 | 1.29 | 1.40 | 1.23 | 1.33 | 0.11 |
| University of California, Berkeley | 2.49 | 1.81 | 6947 | 1523 | 2.35 | 2.54 | 1.30 | 1.40 | 0.11 |
| Washington University in Saint Louis | 2.34 | 1.71 | 4740 | 1060 | 1.60 | 1.77 | 0.94 | 1.03 | 0.10 |
| University of California, Los Angeles | 5.72 | 4.17 | 8666 | 1988 | 2.93 | 3.31 | 0.70 | 0.80 | 0.09 |
| Columbia University | 3.55 | 2.58 | 7993 | 1759 | 2.70 | 2.93 | 1.05 | 1.14 | 0.09 |
| Boston University | 1.64 | 1.20 | 4276 | 931 | 1.45 | 1.55 | 1.21 | 1.30 | 0.09 |
| Northwestern University, Evanston | 1.94 | 1.42 | 6375 | 1357 | 2.15 | 2.26 | 1.52 | 1.60 | 0.08 |
| University of Colorado, Boulder | 1.18 | 0.86 | 3434 | 730 | 1.16 | 1.22 | 1.35 | 1.42 | 0.07 |
| University of Chicago | 3.27 | 2.38 | 4296 | 965 | 1.45 | 1.61 | 0.61 | 0.68 | 0.07 |
| Yale University | 3.02 | 2.20 | 7012 | 1504 | 2.37 | 2.51 | 1.08 | 1.14 | 0.06 |
| University of Pennsylvania | 6.16 | 4.49 | 8862 | 1937 | 3.00 | 3.23 | 0.67 | 0.72 | 0.05 |
| Vanderbilt University | 3.72 | 2.71 | 5237 | 1122 | 1.77 | 1.87 | 0.65 | 0.69 | 0.04 |
| Duke University | 4.80 | 3.50 | 7585 | 1555 | 2.56 | 2.59 | 0.73 | 0.74 | 0.01 |
| Johns Hopkins University | 4.82 | 3.51 | 11020 | 2251 | 3.72 | 3.75 | 1.06 | 1.07 | 0.01 |
| University of Pittsburgh | 1.78 | 1.30 | 6217 | 1265 | 2.10 | 2.11 | 1.62 | 1.63 | 0.01 |
| University of Michigan, Ann Arbor | 6.09 | 4.44 | 10068 | 2048 | 3.40 | 3.41 | 0.77 | 0.77 | 0.00 |
| New York University | 4.34 | 3.16 | 5628 | 1145 | 1.90 | 1.91 | 0.60 | 0.60 | 0.00 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| University of North Carolina, Chapel Hill | 2.70 | 1.97 | 6130 | 1233 | 2.07 | 2.06 | 1.05 | 1.05 | -0.01 |
| University of Washington | 4.36 | 3.18 | 10033 | 1991 | 3.39 | 3.32 | 1.07 | 1.04 | -0.02 |
| University of Rochester | 3.02 | 2.20 | 3086 | 594 | 1.04 | 0.99 | 0.47 | 0.45 | -0.02 |
| University of California, Irvine | 2.36 | 1.72 | 3980 | 780 | 1.35 | 1.30 | 0.78 | 0.76 | -0.03 |
| Cornell University | 1.81 | 1.32 | 7206 | 1440 | 2.44 | 2.40 | 1.84 | 1.82 | -0.03 |
| Emory University | 4.09 | 2.98 | 4735 | 911 | 1.60 | 1.52 | 0.54 | 0.51 | -0.03 |
| Boston College | 0.69 | 0.50 | 789 | 141 | 0.27 | 0.24 | 0.53 | 0.47 | -0.06 |
| University of California, Davis | 3.71 | 2.70 | 6711 | 1243 | 2.27 | 2.07 | 0.84 | 0.77 | -0.07 |
| University of Southern California | 3.51 | 2.56 | 5511 | 1001 | 1.86 | 1.67 | 0.73 | 0.65 | -0.08 |
| Ohio State University, Columbus | 4.92 | 3.59 | 6648 | 1172 | 2.25 | 1.95 | 0.63 | 0.54 | -0.08 |
| Tufts University | 0.78 | 0.57 | 2435 | 462 | 0.82 | 0.77 | 1.45 | 1.36 | -0.09 |
| University of Minnesota, Twin Cities | 2.94 | 2.14 | 6644 | 1212 | 2.25 | 2.02 | 1.05 | 0.94 | -0.10 |
| University of Notre Dame | 0.99 | 0.72 | 2067 | 356 | 0.70 | 0.59 | 0.97 | 0.82 | -0.15 |
| University of Arizona | 1.73 | 1.26 | 4724 | 844 | 1.60 | 1.41 | 1.27 | 1.12 | -0.15 |
| University of Texas, Austin | 2.53 | 1.84 | 5979 | 1045 | 2.02 | 1.74 | 1.10 | 0.94 | -0.15 |
| Brown University | 0.76 | 0.55 | 3112 | 577 | 1.05 | 0.96 | 1.91 | 1.75 | -0.16 |
| University of Florida | 2.43 | 1.77 | 6088 | 1045 | 2.06 | 1.74 | 1.16 | 0.98 | -0.18 |
| University of Wisconsin, Madison | 2.49 | 1.81 | 7310 | 1287 | 2.47 | 2.15 | 1.36 | 1.18 | -0.18 |
| Pennsylvania State University | 4.48 | 3.26 | 7731 | 1127 | 2.61 | 1.88 | 0.80 | 0.58 | -0.22 |
| Michigan State University | 2.09 | 1.52 | 4812 | 746 | 1.63 | 1.24 | 1.07 | 0.82 | -0.25 |
| Case Western Reserve University | 0.86 | 0.63 | 3342 | 581 | 1.13 | 0.97 | 1.80 | 1.54 | -0.26 |
| University of Illinois at Urbana-Champaign | 2.43 | 1.77 | 6224 | 927 | 2.10 | 1.55 | 1.19 | 0.87 | -0.31 |
| Purdue University | 1.64 | 1.20 | 4888 | 724 | 1.65 | 1.21 | 1.38 | 1.01 | -0.37 |
| Carnegie Mellon University | 1.05 | 0.76 | 3353 | 505 | 1.13 | 0.84 | 1.48 | 1.10 | -0.38 |
| Georgia Institute of Technology | 1.35 | 0.98 | 5366 | 814 | 1.81 | 1.36 | 1.84 | 1.38 | -0.46 |
| Total | 137.21 | 100 | 295892 | 59979 | 100 | 100 | | | |

Figure 1. Comparison of institutional rankings based on P/Budget, $P_{top\ 10\%}$/Budget, and the excellence shift




In Figure 1, we compare the rankings of our three (productivity) measures: P/Budget, $P_{top\ 10\%}$/Budget and the excellence shift (last three columns in Table 1). It shows that there is a close relationship between the two publication productivity measures P/Budget and $P_{top\ 10\%}$/Budget (Spearman rank correlation: 0.91). The excellence shift, in contrast, is not correlated with P/Budget (correlation: -0.07) and is only medium-correlated with $P_{top\ 10\%}$/ Budget (correlation: 0.30). Thus, many universities that rank low in terms of productivity might be better in terms of the excellence shift and vice versa.

# Discussion

Although the excellence shift solves the problem of the lack of comparability between universities by making the incomparable comparable, the approach has two disadvantages: (1) since the approach is based on percentages for a certain total, the definition for producing the indicator values should be the same (or similar) at each university. Among other things, the budget should be in the same currency and include the same financial areas (e.g., teaching and research or only research). National databases frequently include these data generated on the basis of a single definition. (2) The excellence shift needs a differentiation between the total and a specific upper portion of the total. This is possible with bibliometrics (as demonstrated here), but not – to our knowledge – with other indicators. Thus, this approach cannot be used for many other indicators often used in productivity analyses, such as research grants and number of students.

# References


Abramo, G., & D'Angelo, C. A. (2016). A farewell to the MNCS and like size-independent indicators. *Journal of Informetrics, 10*(2), 646-651.

Bornmann, L. (2017). Measuring impact in research evaluations: A thorough discussion of methods for, effects of, and problems with impact measurements. *Higher Education, 73*(5), 775-787.

Bornmann, L., & Haunschild, R. (2016). Efficiency of research performance and the glass researcher. *Journal of Informetrics, 10*(2), 652-654.

Bornmann, L., Leydesdorff, L., & Mutz, R. (2013). The use of percentiles and percentile rank classes in the analysis of bibliometric data: opportunities and limits. *Journal of Informetrics, 7*(1), 158-165.

Rhaiem, M. (2017). Measurement and determinants of academic research efficiency: a systematic review of the evidence. *Scientometrics, 110*(2), 581–615. doi: 10.1007/s11192-016-2173-1.

Waltman, L., van Eck, N. J., van Leeuwen, T. N., Visser, M. S., & van Raan, A. F. J. (2011). Towards a new crown indicator: some theoretical considerations. *Journal of Informetrics, 5*(1), 37-47. doi: 10.1016/j.joi.2010.08.001.

Wohlrabe, K., de Moya Anegon, F., & Bornmann, L. (2017). *Are there super-efficient universities in the US science system? An efficiency study based on input and output data. Working Paper*.