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"AN ALTERNATIVE TO FIELD-NORMALIZATION IN THE AGGREGATION OF HETEROGENEOUS SCIENTIFIC FIELDS"

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Abstract. A possible solution to the problem of aggregating heterogeneous fields in the all-sciences case relies on the normalization of the raw citations received by all publications. In this paper, we study an alternative solution that does not require any citation normalization. Provided one uses size- and scale-independent indicators, the citation impact of any research unit can be calculated as the average (weighted by the publication output) of the citation impact that the unit achieves in all fields. The two alternatives are confronted when the research output of the 500 universities in the 2013 edition of the CWTS Leiden Ranking is evaluated using two citation impact indicators with very different properties. We use a large Web of Science dataset consisting of 3.6 million articles published in the 2005-2008 period, and a classification system distinguishing between 5,119 clusters. The main two findings are as follows. Firstly, differences in production and citation practices between the 3,332 clusters with more than 250 publications account for 22.5% of the overall citation inequality. After the standard field-normalization procedure where cluster mean citations are used as normalization factors, this figure is reduced to 4.3%. Secondly, the differences between the university rankings according to the two solutions for the all-sciences aggregation problem are of a small order of magnitude for both citation impact indicators.

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I. INTRODUCTION

As is well known, the comparison of the citation impact of research units is plagued with obstacles of all sorts. For our purposes in this paper, it is useful to distinguish between the following three basic difficulties. (i) How can we compare the citation distributions of research units of different sizes even if they work in the same homogeneous scientific field? For example, how can we compare the output of the large Economics department at Harvard University with the output of the relatively small Economics department at Johns Hopkins? The next two difficulties have to do with the heterogeneity of scientific fields: the well known differences in production and citation practices makes it impossible to directly compare the raw citations received by articles belonging to different fields. Given a classification system, that is, a rule for assigning any set of articles to a number of scientific fields, field heterogeneity presents the following classic hindrances in the evaluation of research units' performance. (ii) How can we compare the citation impact of two research units working in different fields? For example, how can we compare the citation impact of MIT in Organic Chemistry with the citation impact of Oxford University in Statistics and Probability? Finally, (iii) how can we compare the citation impact of two research units taking into account their output in all fields? For example, how can we compare the citation impact of MIT and Oxford University in what we call the *all-sciences* case?

As is well known, the solution to the first two problems requires size- and scale-independent citation impact indicators. We will refer to indicators with these two properties as *admissible* indicators. Given an admissible indicator, in this paper we are concerned with the two types of solutions that the third problem admits. Firstly, the problem can be solved in two steps. One first uses some sort of normalization procedure to make the citations of articles in all fields at least approximately comparable. Then, one applies the citation indicator to each unit's normalized citation distribution. Secondly, consider the Top 10% indicator used in the construction of the influential Leiden and

SCImago rankings.[1] In the Leiden Ranking this indicator is defined as "*The proportion of publications of a university that, compared with other similar publications, belong to the top 10% most frequently cited…Publications are considered similar if they were published in the same field and the same publication and if they have the same document type*" (Walman *et al.*, 2012a).[2] Note that this way of computing this particular indicator inn the all-sciences case does not require any kind of prior citation normalization.[3] For our purposes, it is useful to view this procedure as the average (weighted by the publication output) of the unit's Top 10% performance in each field. We note that this important precedent can be extended to *any* admissible indicator. Thus, given a classification system and an admissible citation indicator, we can compute the citation impact of a research unit in the all-sciences case as the appropriate weighted average of the unit's citation impact in each field. Independently of the conceptual interest of this proposal, we must compare the consequences of adopting it versus the possibility of following a normalization procedure.

Intuitively, the better the performance of the normalization procedure in eliminating the comparability difficulties across fields, the smaller the differences will be between the two approaches. Using a measuring framework introduced in Crespo *et al.* (2013), recent research has established that different source (or citing-side) and target (or cited-side) normalization procedures perform quite well in eliminating most of the effect in overall citation inequality that can be attributed to differences in production and citation practices between fields (Waltman & Van Eck, 2013, Crespo *et al.*, 2013, 2014, and Li *et al.*, 2013). Therefore, we expect that the differences between the two approaches for solving the all-sciences aggregation problem would be of a small order of magnitude. However, this is an

[1] SCImago is a research group from the *Consejo Superior de Investigaciones Científicas*, University of Granada, Extremadura, Carlos III (Madrid) and Alcalá de Henares in Spain. The *SCImago Institutions Rankings* (SIR; www.scimagoir.com) is a bibliometric ranking of research institutions based on Elsevier's Scopus database.

[2] A similar definition is applied in the SCImago ranking (Bornmann *et al.*, 2012), as well as in the InCites software (see 'percentile I subject area in http://incites.isiknowledge.com/common/help/h_glossary.htlm).

[3] Naturally, everything that we say for the all-sciences case can be equally applied at other aggregation levels, as in the case of aggregating articles in Organic Chemistry, Inorganic Chemistry, Chemical Engineering, and other related sub-fields into the discipline of Chemistry.

empirical question that has never been investigated before. To confront this question, in this paper we conduct the following exercise.

• Ruiz-Castillo & Waltman (2015) apply the publication-level algorithmic methodology introduced by Waltman & Van Eck (2012) to a Web of Science (WoS hereafter) dataset consisting of 9.4 million publications from the 2003-2012 period. This is done along a sequence of twelve independent classification systems in each of which the same set of publications is assigned to an increasing number of clusters. In this paper, we use the classification system recommended in Ruiz-Castillo & Waltman (2015), consisting of 5,119 clusters. For the evaluation of research units' citation impact, we focus on the 3.6 million publications in the 2005-2008 period, and the citations they receive during a five-year citation window for each year in that period.

• Our research units are the 500 universities in the 2013 edition of the CWTS Leiden Ranking (Waltman *et al.*, 2012a). We analyze the approximately 2.4 million articles –about 67% of the total– for which at least one author belongs to one of these universities. We use a fractional counting approach to solve the problem of the assignment of responsibility for publications with several co-authors working in different institutions. The total number of articles corresponding to the 500 universities is approximately 1.9 million articles –about 50% of the total.

• We evaluate the citation impact of each university using two admissible indicators. Firstly, the Top 10% indicator already mentioned. Secondly, one characteristic of this indicator is that it is not monotonic in the sense that it is invariant to any additional citation that a high-impact article might receive. Consequently, we believe that it is interesting to use a second indicator possessing this property. In particular, we select a member of the Foster, Greer, and Thorbecke (FGT hereafter) family, introduced in Albarrán *et al.* (2011a). We apply this indicator to the set formed by the 10% of the most highly cited publications in the world, referred to as the set of high-impact articles.

• Li *et al.* (2013) indicate that the best alternative among a wide set of field-normalization procedures is the two-parameter system developed in Radicci & Castellano (2012).[4] However, different results indicate that the standard, one-parameter field-normalization procedure, in which normalized citation scores in every field are equal to the original raw citations divided by the field mean citation, exhibits a good performance (Radicchi *et al.*, 2008, Crespo *et al.*, 2013, 2014, Li *et al.*, 2013, and Ruiz-Castillo, 2014). Given its simplicity and good performance, in this paper we adopt this procedure in the solution to the all-sciences aggregation problem.

• An indicator is said to be additively decomposable if, for any partition of a citation distribution into a number of disjoint sub-groups, the citation impact of the entire distribution can be expressed as the average (weighted by the subgroups' output) of the sub-groups' citation impact. As will be seen below, the fact that both of our indicators possess this property facilitates the comparability of the two solutions to the all-sciences aggregation problem that constitutes the main aim of the paper.

• We present two types of results. Firstly, we assess the performance of the standard field-normalization procedure in facilitating the comparability of the citations received by articles belonging to different clusters. Secondly, we assess the consequences of adopting the two solutions to the all-sciences aggregation problem by comparing the corresponding university rankings according to the two admissible citation impact indicators.

• The two main findings are the following. Firstly, differences in production and citation practices between 3,332 clusters with more than 250 publications account for 22.5% of the overall citation inequality. After the standard field-normalization procedure, where cluster mean citations are used as normalization factors, this figure is reduced to 4.3%. Secondly, the differences between the

[4] Target (or cited-side) normalization procedures depend on a given classification system including a number of heterogeneous fields. To recognize this feature, it is useful to refer to these procedures as field-normalized normalization procedures. This is the practice we follow in this paper.

university rankings obtained with the two methods for solving the all-sciences aggregation problem is of a very small order of magnitude for both citation impact indicators.

The rest of the paper is organized into four sections. Section II introduces the citation impact indicators, and its properties. Section III presents the two solutions to the all-sciences aggregation problem. Section IV describes the data, and includes the empirical results, while Section V concludes.

II. CITATION IMPACT INDICATORS

II.1. Notation

It is now convenient to introduce some notations. Given a set D of N distinct articles, and J scientific fields indexed by $j = 1,\ldots, J$, a *classification system* is an assignment of articles in D to the J fields. Let I be the number of research units, indexed by $i = 1,\ldots, I$. For simplicity, in this Section we assume that there is no co-authorship, so that each article in D belongs to a single unit in I. Let c_{ijk} be the number of citations received by the k-th article of unit i in field j. Then $\boldsymbol{c}_{ij} = \{c_{ijk}\}$ denotes the *citation distribution of unit i in field j*, while $\boldsymbol{c}_j$ denotes the *citation distribution of field j*, that is, the union of all research units' citation distributions in that field: $\boldsymbol{c}_j = \cup_i \{\boldsymbol{c}_{ij}\}$. Under the simplifying assumption of no co-authorship, the set of distributions $\boldsymbol{c}_{ij}$ form a partition of $\boldsymbol{c}_j$.[5] Finally, let $\boldsymbol{C} = \cup_j \{\boldsymbol{c}_j\} = \cup_i \cup_j \{\boldsymbol{c}_{ij}\}$ be the *overall citation distribution*, or the citation distribution in the all-sciences case. For later reference, let N_{ij} be the number of articles in distribution $\boldsymbol{c}_{ij}$, let $N_i = \Sigma_j N_{ij}$ be the total number of articles published by unit i, and let $N_j = \Sigma_i N_{ij}$ be the total number of articles in field j. Of course, the total number of articles in the all-sciences case is $N = \Sigma_i \Sigma_j N_{ij}$.

In our context, where in every field j we have $\boldsymbol{c}_j = \cup_i \{\boldsymbol{c}_{ij}\}$, the evaluation of any citation distribution is done taking into account a key characteristic of distribution $\boldsymbol{c}_j$, say θ_j. Thus, a *citation*

[5] More generally, in this Section we assume that the assignment of articles in D to the I research units is such that the set of distributions $\boldsymbol{c}_{ij}$ form a partition of $\boldsymbol{c}_j$.

impact indicator is a function F defined in the product space of all citation distributions and the characteristic space, so that –given θ_j– the expression $F_{ij} = F(\mathbf{c}_{ij}; \theta_j)$ denotes the citation impact of unit i in field j, while $F_j = F(\mathbf{c}_j; \theta_j)$ denotes the citation impact of field j as a whole. To clarify this notion, consider the following three indicators that will be used in this paper.

1. Let μ_{ij} and μ_j be the mean citation of distributions $\mathbf{c}_{ij}$ and $\mathbf{c}_j$, respectively. The *Relative mean citation indicator*, M, is defined as

$$M_{ij} = M(\mathbf{c}_{ij}; \mu_j) = \mu_{ij}/\mu_j. \tag{1}$$

In this case, $\theta_j = \mu_j$. For field j as a whole, $M_j = \mu_j/\mu_j = 1$.

2. Let X_j be the set of the 10% most cited articles in citation distribution $\mathbf{c}_j$, and let X_{ij} be the sub-set of articles in X_j corresponding to unit i, so that $X_j = \cup_i\{X_{ij}\}$ with X_{ij} non-empty for some i. If n_{ij} is the number of articles in X_{ij}, then the *Top 10% indicator, T,* is defined as

$$T_{ij} = T(\mathbf{c}_{ij}; X_j) = n_{ij}/N_{ij}. \tag{2}$$

In this case, $\theta_j = X_j$. If $n_j = \Sigma_i\, n_{ij}$ is the number of articles in X_j, then for field j as a whole, $T_j = T(\mathbf{c}_j; X_j) = n_j/N_j = 0.10$.

3. Let z_j be the *Critical Citation Line* –CCL hereafter– for citation distribution $\mathbf{c}_j$, and denote the articles in $\mathbf{c}_j$ with citations equal to or greater than z_j as *high-impact articles*. For any high impact article with citations c_{il}, the *CCL normalized high-impact gap* is defined as $(c_{il} - z_j)/z_j$. Consider the family of FGT indicators introduced in Albarrán *et al.* (2011a) as functions of normalized high-impact gaps. The second member of this family, referred to as the *Average of high-impact gaps*, *A*, is defined as

$$A_{ij} = A(\mathbf{c}_{ij}; z_j) = (1/N_{ij})[\Sigma_l\,(c_{il} - z_j)/z_j], \tag{3}$$

where the sum is over the high-impact articles in c_j that belong to citation distribution c_{ij}. In this case, $\theta_j = z_j$. For the entire field j as a whole, we have $A_j = A(c_j; z_j) = (1/N_j)[\Sigma_k (c_k - z_j)/z_j]$, where the sum is over the high-impact articles in c_j.

To facilitate the comparison with T_{ij}, in the sequel we will always fix z_j as the number of citations of the article in the 90th percentile of citation distribution c_j. In that case, the set of high-impact articles coincides with the set of the 10% most cited articles in citation distribution c_j. In other words, for both indicators we have $\theta_j = z_j$. The two main differences between T and A are the following. Firstly, one or more citations received by a high-impact article increases A_{ij} but does not change T_{ij}. In other words, A is monotonic but T is not. Secondly, T is more robust to extreme observations than A.

II.2. Size- and scale-independence

Consider the following two difficulties for comparing the citation impact of any pair of research units: the two units may be of different sizes, and if they work in different fields, then their raw citations are not directly comparable. To see how to overcome the first difficulty, assume that we have two citation distributions c_{uj} and c_{vj} for units u and v in field j. In the example given in the Introduction, u is Harvard, v is John Hopkins, and j is Economics. Given any distribution c, let c^r be the r-th replica of it. Given θ, an indicator F is said to be *size-independent* if, for any citation distribution c, $F(c^r; \theta) = F(c; \theta)$ for all r. Next, let $c^r{}_{uj}$ be the r-replica of distribution c_{uj} with $r = N_{vj}$, and let $c^t{}_{vj}$ be the t-replica of distribution c_{vj} with $t = N_{uj}$. Now $c^r{}_{uj}$ and $c^t{}_{vj}$ have the same size equal to N_{vj} times N_{uj}. Thus, if F is size-independent, so that $F(c^r{}_{uj}; \theta_j) = F(c_{uj}; \theta_j)$ and $F(c^t{}_{vj}; \theta_j) = F(c_{vj}; \theta_j)$, the first difficulty is overcome.

To see how to handle the second difficulty, let $\mathbf{c}_{ij}$ and $\mathbf{c}_{lw}$ be two citation distributions for unit i in field j, and for unit v in field w. In the example mentioned in the Introduction, i = MIT, j = Organic Chemistry, v = Oxford University, and w = Statistics and Probability. An indicator F is said to be *scale-independent* if, for any citation distribution $\mathbf{c}$, any characteristic θ, and any $\lambda > 0$, $F(\lambda \mathbf{c}; \lambda\theta) = F(\mathbf{c}; \theta)$. Next, let $b = \theta_j/\theta_w$, and consider the normalized distribution $\mathbf{c'}_{ij} = \{c'_{ijk}\}$, where $c'_{ijk} = c_{ijk}/b$ for all k = 1,.., N_{ij}. Note that $\theta'_j = \theta_j/b = \theta_w$, so that citation distributions $\mathbf{c'}_{ij}$ and $\mathbf{c}_{lw}$ are now comparable under θ_w. Thus, if F is scale-independent, so that $F(\mathbf{c}_{ij}; \theta_j) = F(\mathbf{c'}_{ij}; \theta'_j) = F(\mathbf{c'}_{ij}; \theta_w)$, the second difficulty is overcome.

An indicator F is said to be *admissible* if it is size- and scale-independent. The *h*-index is an important example of an indicator that is neither size- nor scale-independent. On the contrary, the three indicators defined in expressions (1), (2), and (3) are good examples of admissible indicators.

II.3. The additive decomposability property

The following property is very convenient. Given θ, an indicator F is said to be *additively decomposable* if for any partition of a citation distribution $\mathbf{c}$ into G disjoint sub-groups, indexed by g = 1,..., G, the citation impact of distribution $\mathbf{c}$ can be expressed as follows:

$$F(\mathbf{c}; \theta) = \Sigma_g (n_g/n) F(\mathbf{c}_g; \theta),$$

where n_g is the number of publications in sub-group g, and $n = \Sigma_g n_g$ is the number of publications in distribution $\mathbf{c}$. To illustrate the usefulness of this property, consider the following three situations in which the indicator F is assumed to be admissible.

A. Under our assumptions, in every field j we have $\mathbf{c}_j = \cup_i \{\mathbf{c}_{ij}\}$, and the distributions $\mathbf{c}_{ij}$, i = 1,…, I, constitute a partition of $\mathbf{c}_j$. If F is additively decomposable, then we can write

$$F(\mathbf{c}_j; \theta_j), = \Sigma_i (N_{ij}/N_j) F(\mathbf{c}_{ij}; \theta_j). \tag{4}$$

This is a very natural condition, indicating that the citation impact of field j as a whole can be expressed as the weighted average of the research units' citation impact under a common θ_j.

B. Assume that country v consists of R regions, indexed by $r = 1,\ldots, R$, and assume that the R citation distributions in field j, $\boldsymbol{c}_{vrj}$, form a partition of the citation distribution of country v in that field, $\boldsymbol{c}_{vj}$. If F is additively decomposable, then we can write

$$F(\boldsymbol{c}_{vj}; \theta_j) = \Sigma_r (N_{vrj}/N_v)F(\boldsymbol{c}_{vrj}; \theta_j), \tag{5}$$

where N_{vrj} is the number of publications in region r, so that $N_{vj} = \Sigma_r N_{irj}$. Equation (5) indicates that the citation impact of country v in field j can be expressed as the weighted average of the regions' citation impact in field j under a common θ_j.

C. Assume that $\boldsymbol{c}_j$ can be partitioned into S heterogeneous sub-fields, indexed by $s = 1,\ldots, S$, so that $\boldsymbol{c}_j = \cup_s \{\boldsymbol{c}_{sj}\}$, where $\boldsymbol{c}_{sj}$ is the citation distribution of sub-field s in field j. If F is additively decomposable, then we can write

$$F(\boldsymbol{c}_j; \theta_j) = \Sigma_s (N_{sj}/N_j)F(\boldsymbol{c}_{sj}; \theta_j), \tag{6}$$

where N_{sj} is the number of publications in sub-field s, so that $N_j = \Sigma_s N_{sj}$. Equation (6) indicates that the citation impact in field j as a whole can be expressed as the weighted average of the sub-field citation impact values. However, this expression adds citation impact values corresponding to raw citation distributions of heterogeneous sub-fields using as reference the characteristic θ_j at the field level. Thus, although this decomposition is mathematically possible, it does not provide a satisfactory solution to the aggregation problem mentioned in note 1. Such a solution will have to wait until the next Section.

Finally, note the following two points. Firstly, equation (4) can be written as follows:

$$\Sigma_i (N_{ij}/N_j) [F(\boldsymbol{c}_{ij}, \theta_j)/F(\boldsymbol{c}_j; \theta_j)] = 1,$$

so that the value one can serve as a benchmark for evaluating the research units in the usual way. The same can be said of equations (5) and (6). Secondly, the three admissible indicators introduced in expressions (1), (2), and (3) are additively decomposable.

III. THE SOLUTIONS TO THE ALL-SCIENCES AGGREGATION PROBLEM

III.1. The solution to the all-sciences aggregation problem using the standard field-normalization procedure

Differences in production and citation practices across fields makes it impossible to directly aggregate the raw citations received by articles in different fields. In order to solve the all-sciences aggregation problem, one possibility is to use a normalization procedure. As indicated in the Introduction, given its simplicity and good performance, in this paper we adopt the standard field-normalization procedure in which the raw citation scores in any field are normalized using the field mean citation as the normalization factor.

Formally, for any article k in citation distribution $\mathbf{c}_{ij}$, the normalized number of citations c^*_{ijk} is defined as

$$c^*_{ijk} = c_{ijk}/\mu_j.$$

The *normalized overall citation distribution* is $\mathbf{C^*} = \cup_i \{\mathbf{c^*}_i\}$, where $\mathbf{c^*}_i = \cup_j \cup_k \{c^*_{ijk}\}$ is the *normalized citation distribution of unit i in the all-sciences case*. Since normalized citations are now comparable, it makes sense to apply any indicator to citation distribution $\mathbf{c^*}_i$. Given the key characteristic θ^* of distribution $\mathbf{C^*}$, for any i, let $F^*_i = F(\mathbf{c^*}_i; \theta^*)$ be the citation impact of distribution $\mathbf{c^*}_i$ according to the indicator F. For any pair of research units u and v, the citation impact values F^*_u and F^*_v are now comparable, and can be used to rank the two units in question.[6] Since F is assumed to be additively decomposable, we can write

[6] The aggregation of S heterogeneous sub-fields examined in situation C in Sub-section II.3, admits a similar solution: $F(\mathbf{c^*}_j; \theta^*) = \Sigma_s (N_{sj}/N_j)F(\mathbf{c^*}_{sj}; \theta^*)$.

$$F^* = F(\mathbf{C}^*;\ \theta^*) = \Sigma_i\ (N_i/N)F^*_i.$$

Thus, if we rank universities by the ratio F^*_i/F^*, $i = 1,\ldots, I$, then the value one can serve as a benchmark for evaluating the research units in the usual way.

For later reference, since $\mathbf{c}^*_i = \cup_j \{\mathbf{c}^*_{ij}\}$, for each i we can write:

$$F^*_i = F(\mathbf{c}^*_i;\ \theta^*) = \Sigma_j\ (N_{ij}/N_i)\ F(\mathbf{c}^*_{ij};\ \theta^*) = \chi_i(\ \mathbf{c}^*_{ij}, j = 1,\ldots, J,\ \theta^*). \qquad (7)$$

Note that, for each i, F^*_i depends only on $\mathbf{c}^*_{ij}$, $j = 1,\ldots, J$, and the common yardstick θ^*, that is, $F^*_i = \chi_i(\ \mathbf{c}^*_{ij}, j = 1,\ldots, J,\ \theta^*)$.

III.2. A solution to the all-sciences aggregation problem without field-normalization

For any unit i in any field j, given θ_j the expression $F_{ij} = F(\mathbf{c}_{ij};\ \theta_j)$ is the citation impact of i in j according to indicator F. A convenient measure of citation impact for unit i in the all-sciences case, Φ_i, can be defined as the weighted average of the values F_{ij} achieved in all fields, with weights equal to the relative importance of each field in the total production of unit i. Adding up "admissible" $F(\mathbf{c}_{sj};\ \theta_j)$ values for different fields under characteristic θ_j in each of them should pose no problem at all. Note that this measure, F_i, is a function φ_i of every citation distribution $\mathbf{c}_{ij}$ and every θ_j for all $j = 1,\ldots, J$:

$$\Phi_i = \varphi_i(\mathbf{c}_{ij},\ \theta_j, j = 1,\ldots, J) = \Sigma_j\ (N_{ij}/N_i)F_{ij}.^7 \qquad (8)$$

After the standard field-normalization procedure, we have $\mathbf{C}^* = \cup_j \{\mathbf{c}^*_j\}$, where $\mathbf{c}^*_j = \cup_i \cup_k \{c^*_{ijk}\}$ is the *normalized citation distribution of field j*. Let θ^*_j be the characteristic of $\mathbf{c}^*_j$ analogous to the characteristic θ^* of $\mathbf{C}^*$, so that $\theta^* = \Sigma_j\ (N_j/N)\theta^*_j$, and $\theta^*_j = \theta_j/\mu_j$. Therefore, since F is scale-independent, $F_{ij} = F(\mathbf{c}_{ij};\ \theta_j) = F(\mathbf{c}^*_{ij};\ \theta^*_j)$ for all j. Hence, equation (8) can ne written as follows:

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[7] The aggregation of S heterogeneous sub-fields examined in situation C in Sub-section II.3, admits a similar solution: $F(\mathbf{c}_j;\ \theta_j) = \Sigma_s\ (N_{sj}/N_j)F(\mathbf{c}_{sj};\ \theta_{sj})$, where θ_{sj} is the characteristic of citation distribution $\mathbf{c}_{sj}$ at the sub-field level for every $j = 1,\ldots, J$.

$$\Phi_i = \varphi(c_{ij}, \theta_j, j = 1,\ldots, J) = \Sigma_j (N_{ij}/N_i) F(c^*_{ij}; \theta^*_j). \quad (9)$$

The comparison of expressions (7) and (9) illustrate the differences between the two solutions to the all-sciences aggregation problem when the evaluation of the units' citation impact is made with additively decomposable indicators. For any i, $F(c^*_{ij}; \theta^*)$ in equation (7) measures the citation impact of unit i in field j using as reference the characteristic θ^* of the overall normalized citation distribution C^*. However, $F(c^*_{ij}; \theta^*_j) = F(c_{ij}; \theta_j)$ in equation (9) measures the citation impact of unit i in field j using as reference the characteristic θ^*_j of each citation distribution c^*_j or, what is the same, using as reference the characteristic θ_j of each citation distribution c_j prior to applying the standard field-normalization procedure. Consequently, computing $\Phi_i = \varphi(c_{ij}, \theta_j, j = 1,\ldots, J)$ avoids the possible errors committed in the normalization of raw citation scores using the procedure in (7).

It is convenient to compute the weighted average of the F_i values as follows:

$$\Phi = \Sigma_i (N_i/N)\ \Phi_i = \Sigma_i (N_i/N)\ \Sigma_j (N_{ij}/N_i)F_{ij} = \Sigma_i \Sigma_j (N_{ij}/N)F_{ij}. \quad (10)$$

Thus, as before, if we rank universities by the ratio F_i/F, $i = 1,\ldots, I$, then the value one can serve as a benchmark for evaluating the research units in the usual way.

In practice, we have information concerning some –the 500 LR universities– but not all research units. Therefore, we cannot compute Φ using expression (10). Starting from that expression, we have

$$\Phi = \Sigma_i \Sigma_j (N_{ij}/N)F_{ij} = \Sigma_j (N_j/N)\ \Sigma_i (N_{ij}/N_j)F_{ij}.$$

Since $c_j = \cup_i \{c_{ij}\}$, and F is additively decomposable, $\Sigma_i (N_{ij}/N_j)F_{ij} = F_j$, where $F_j = F(c_j, \theta_j)$ can be computed with our data. Therefore, we can compute Φ as follows

$$\Phi = \Sigma_j (N_j/N)\ F_j.$$

On the other hand, since $F_j = \mathrm{F}(c_j, \theta_j) = F^*_j = \mathrm{F}(c^*_j, \theta^*_j)$, we have $F^* = \Phi$. Finally, note that when $F = M$, $F^* = \Phi = 1$, while when $F = T$, $F^* = \Phi = 0.10$.

III.3. The aim of the paper

The main aim of this paper is the comparison between the rankings of research units obtained with and without the standard field-normalization procedure, $(F^*_1, \ldots, F^*_I)$ and $(\Phi_1, \ldots, \Phi_I)$, respectively. To understand the way the results will be presented, recall that, for any j, X_j is the set of high-impact articles in distribution c_j, that is, the set of articles in c_j with citations equal to or greater than z_j, or the set of the 10% most cited articles in c_j. Let us denote by $X = (X_1, \ldots, X_j, \ldots, X_J)$ the set of high-impact articles in the all-sciences case. On the other hand, let Y be the set of the 10% most cited articles in the overall normalized citation distribution $\mathbf{C}^* = \cup_j \{c^*_j\}$, and let Y_j be the sub-set of articles in $\mathbf{Y}$ belonging to field j, so that $Y = (Y_1, \ldots, Y_j, \ldots, Y_J)$.

Under the universality condition, that is, if all fields are equally distributed except for a scale factor, then the normalization procedure will eliminate all differences between citation practices across clusters, and the two solutions to the all-sciences aggregation problem will coincide. The reason is that in this situation we would have $z^*_j = z_j/\mu_j = z^*$ for all j. Consequently, $Y_j = X_j$ for all j, and $Y = X$. Since citation distributions c^*_{ij} and c_{ij} have the same number of articles and our indicators are a function solely of high-impact articles, we would have $F_{ij} = F(c_{ij}; z_j) = F(c^*_{ij}; z^*_j) = F(c^*_{ij}; z^*) = F^*_{ij}$ for all i and j. In view of equations (7) and (8), we would have $F^*_i = \Phi_i$ for all i. In other words, the rankings $(F^*_1, \ldots, F^*_I)$ and $(\Phi_1, \ldots, \Phi_I)$ will be identical.

As we know, in practice the universality condition is not satisfied (Albarrán *et al.*, 2011b, Waltman *et al.*, 2012b, Thelwall & Wilson, 2014, and Brzezinski, 2015). Consequently, the performance of the field-normalization procedure cannot be perfect, and the sets $\mathbf{Y}$ and $\mathbf{X}$ will not coincide. In this situation, we should measure the consequences of adopting the two solutions to the all-sciences aggregation problem using indicators with different properties. The reason, of course, is that whenever Y and X differ, that is, when the set of high-impact articles under the two solutions differ, the consequences for the university rankings might be of a different order of magnitude depending on the citation impact indicator we use.

Finally, note that, generally, $F^*_i \neq F_i$ for all $i = 1,\ldots, I$. However, it is easy to establish that this is not the case for the relative mean indicator M. As a matter of fact,

$$M^*_i = (1/N_i)\, \Sigma_j\, \Sigma_k\, c^*_{ijk} = (1/N_i)\, \Sigma_j\, \Sigma_k\, c_{ijk}/\mu_j$$

is simply the Mean Normalized Citation Score indicator. However,

$$M_i = \Sigma_j\, (N_{ij}/N_i)\, M_{ij} = \Sigma_j\, (N_{ij}/N_i)\, (\mu_{ij}/\mu_j) = (1/N_i)\, \Sigma_j\, \Sigma_k\, c_{ijk}/\mu_j = M^*_i.$$

Therefore, in the empirical part of the paper we will only study the university rankings obtained with the indicators T and A, namely, the top 10% and the average of high-impact gaps.

IV. EMPIRICAL RESULTS

IV.1. The data and descriptive statistics

Our dataset results from the application of a publication-level algorithmic methodology to 9,446,622 distinct articles published in 2003-2012 (see Ruiz-Castillo & Waltman, 2015). Publications in local journals, as well as popular magazines and trade journals, have been excluded (see Ruiz-Castillo & Waltman, 2015, for the details). We work with journals in the sciences, the social sciences, and the arts and humanities, although many arts and humanities journals are excluded because they are of a local nature. The classification system consists of 5,119 clusters, and citation distributions refer to the citations received by these articles during a five-year citation window for each year in that period. In this paper, we focus on the set of 3,614,447 distinct articles published in the period 2005-2008. In terms of the notation introduced in Section II.1, we have $\boldsymbol{C} = \cup_j \{c_j\} = (c_1,\ldots, c_N)$ with $J = 5{,}119$, and $N = 3{,}614{,}447$.

We sort clusters in decreasing order by size, where size is measured as the number of publications, and group clusters into ten decile classes, indexed by $d = 1,\ldots, 10$.. For each decile, the average number of publications per cluster, denoted by m_d, and the average number of citations per publication, denoted by μ_d, are in Table 1. Note the presence of a large number of small clusters with less than or equal to 100 publications (typically accompanied by a low mean citation per article). However, the set of small clusters includes a very small proportion of the 3.6 million articles in the entire dataset (see row D in Table 1).

Table 1 around here

The research units are universities. As in Waltman *et al.* (2012b), publications are assigned to universities using the fractional counting method that takes into account the address lines appearing in each publication. We are only concerned with the 2,420,054 distinct articles, or 67% of the total, with at least one address line belonging to an LR university. Any article of this type is fully assigned to an LR university only if all addresses mentioned in the publication belong to the university in question. If a publication is co-authored by two or more LR universities, then it is assigned fractionally to all of them in proportion to the number of address lines in each case. For example, if the address list of an article contains five addresses and two of them belong to a particular university, then 0.4 of the article is assigned to this university, and only 0.2 of the article is assigned to each of the other three universities. Finally, consider a publication co-authored by an LR university and an unknown number of other institutions outside the Leiden Ranking. Assume, for example, that the publication has four address lines, two of which correspond to the LR university. In this case, only 0.5 of the article will be assigned to the LR university. This procedure implies that the total fractional number of articles assigned to LR universities will be smaller than the total number of articles with at least one address line belonging to an LR university. It turns out that this number is 1,886,106.1, or 52.2% of the total. The distribution of this total among the 500 universities is in columns 1 and 2 in Table A in the Appendix.

Finally, we compare the skewness and citation inequality of the three distributions consisting of 3.6, 2.4, and 1.9 million articles using the Characteristic Scores and Scales approach (Schubert *et al.*, 1987), as well as two indicators of citation inequality and skewness that are robust to extreme observations (Groeneveld and Meeden, 1984). The results are in Table B in the Appendix. Interestingly enough, the skewness and citation inequality of the three distributions are of the same order of magnitude.

IV.2. The performance of the standard field-normalization procedure

We can estimate the impact of the standard field-normalization procedure using the measurement framework introduced in Crespo *et al.* (2013). We first estimate the effect on overall citation inequality that can be attributed to differences in production and citation practices between clusters through the term *IDCC* (*I*nequality due to *D*ifferences in *C*itation impact between *C*lusters). Then, we assess the performance of the standard field-normalization procedure by the reduction it induces in the *IDCC* term. In applications, it is convenient to partition each cluster citation distribution into 100 percentiles, indexed by π = 1,..., 100. Given the many clusters with very few publications (see Table 1), we apply this method to the citation distribution ***C'*** restricted to the 3,332 clusters with more than 250 publications. This distribution includes 3,441,666 million publications, or 95.2% of the total.

Assume for a moment that, in any cluster *j*, we disregard the citation inequality within every percentile by assigning to every article in that percentile the mean citation of the percentile itself, μ_j^{π}.

The interpretation of the fact that, for example, $\mu_j^{\pi} = 2\ \mu_i^{\pi}$ is that, on average, the citation impact of cluster j is twice as large as the citation impact of cluster l in spite of the fact that both quantities represent a common underlying phenomenon, namely, the same *degree of citation impact* in both clusters. In other words, for any π, the distance between μ_j^π and μ_l^π is entirely attributable to the differences in the production and citation practices that prevail in the two clusters for publications having the same degree of excellence. Thus, the citation inequality between clusters at each percentile, denoted by $I(\pi)$, is entirely attributable to the differences in citation practices between the 3,332 clusters holding constant the degree of excellence in all clusters at quantile π. Hence, the term *IDCC*, which is equal to a certain weighted average of these quantities, provides a good measure of the total impact on overall citation inequality that can be attributed to such differences (for details, see Crespo *et al.*, 2013). We use the ratio

$$IDCC/I(\mathbf{C'}) \tag{11}$$

to assess the relative effect on overall citation inequality, $I(\mathbf{C'})$, attributed to the differences in citation practices between clusters. Finally, we are interested in estimating how important scale differences between cluster citation distributions are in accounting for the effect measured by expression (11). For that purpose, we use the relative change in the *IDPC* term, that is, the ratio

$$[IDCC - IDCC^*]/IDCC, \tag{12}$$

where *IDCC** is the term that measures the effect on overall citation inequality attributed to the differences in cluster distributions after applying the standard field-normalization procedure.

It should be noted that, using the size- and scale-independent technique known as Characteristic Scores and Scales, Ruiz-Castillo & Waltman (2015) show that, as in previous research, the 4,161 significant clusters with more than 100 publications are highly skewed and similarly distributed. Since the more similar citation distributions are, the better should work any normalization procedure, we expect reasonably good results in our case. The estimates of expressions (11) and (12) are presented in

Table 2. For comparison purposes, we include the results from Crespo *et al.* (2013) and Li *et al.* (2013) for 219 and 172 WoS sub-fields, respectively.

Table 2 around here

It can be observed that the effect of the differences in citation practices between the 3,332 clusters represents 22.5% of overall citation inequality, a greater percentage than what has been found in the previous literature for 219 or 172 sub-fields. Nevertheless, the standard field-normalization procedure reduces this effect down to 4.3% of the new overall citation distribution, which is quite an achievement. On the other hand, field-normalization generates an 84.3% reduction of the *IDCC* term, a comparable figure with what is found in the previous literature. Thus, for the largest 3,332 of the 5,119 clusters, the performance of the standard field-normalization procedure is reasonably good.

Finally, it is very instructive to study how $I(\pi)$ changes with π both before and after the standard field-normalization. The results appear in Figure 1 (since $I(\pi)$ is very high for $\pi < 25$, for clarity these percentiles are omitted from Figure 2), which warrants the following two comments. Firstly, the significant impact of field-normalization is readily apparent. Secondly, it is useful to informally partition the support of our citation distributions into the following three intervals: [0, 47], [48, 97], and [98, 100]. In the first and the third one, $I(\pi)$ values are very high. This means that, since in these two intervals cluster citation distributions differ by more than a scale factor, the universality condition can hardly be satisfied in them. However, $I(\pi)$ is approximately constant for a wide range of intermediate values in the second interval.

Figure 1 around here

IV.3. Differences between the two approaches

In spite of the good performance of the standard field-normalization procedure we should not forget that the differences in production and citation practices between clusters remaining after normalization are still responsible for 4.3% of the overall citation inequality $I(\mathbf{C'})$. Moreover, we should take into account that the 1,787 clusters with less than 250 publications must be brought back into the analysis. Therefore, we expect that sets of high-impact articles before and after the field-normalization introduced in Section III.3, namely, the sets $\boldsymbol{X} = (X_1,\ldots, X_j,\ldots, X_J)$ and $\boldsymbol{Y} = (Y_1,\ldots, Y_j,\ldots, Y_J)$, present some differences worth studying. As a benchmark, we first define the set $\boldsymbol{B}$ of high-impact articles –that is, the 10% most cited articles– in the ordered overall citation distribution C where articles from all clusters are ordered according to their raw citations prior to the application of any normalization procedure. Let B_j be the subset of $\boldsymbol{B}$ with articles in field j, possibly empty for many j, so that $\boldsymbol{B} = (B_1,\ldots, B_j,\ldots, B_J)$.[8] Next, we compare the sets $\boldsymbol{X}$ and $\boldsymbol{Y}$, and $\boldsymbol{X}$ and $\boldsymbol{B}$ from the following two points of view.

1. In the first place, we compute the number of clusters where $\boldsymbol{Y}$ and $\boldsymbol{B}$ are empty, as well as the number of articles in the intersections between the two pairs: $\boldsymbol{X}\cap\boldsymbol{B}$, and $\boldsymbol{X}\cap\boldsymbol{Y}$. The results are in Table 3.A. Two comments are in order. Firstly, although the number of empty clusters in $\boldsymbol{B}$ is relatively large, the percentage of missing articles is small: only 2.7% of all high-impact articles in $\boldsymbol{X}$ are missed for this reason. This percentage is negligible for $\boldsymbol{Y}$. Secondly, the percentage of articles in $\boldsymbol{X}\cap\boldsymbol{B}$ is close to two thirds of the total. Given the way $\boldsymbol{B}$ has been constructed, this is somewhat surprising. In turn, the set $\boldsymbol{X}\cap\boldsymbol{Y}$ represents 94.8% of the total. Thus, only approximately 5% of articles in X are not found in the normalized set Y.

It is worth reviewing the situation when we restrict the attention to the 3,332 clusters with more than 250 publications, that is, when the overall citation distribution is $\boldsymbol{C'}$. The results for the corresponding sets X', $\boldsymbol{Y'}$, and $\boldsymbol{B'}$ are in Table 3.B. The number of empty clusters in B' decreases

[8] Due to ties, as well as the presence of clusters with fewer than 10 publications, it is usually not possible to make an exact distinction between publications that belong to the top 10% and publications that do not belong to that set in every cluster. In order to end up with exactly 10% top publications in the dataset, we select the top 10% publications in each cluster following the fractional procedure recommended in Waltman & Schreiber (2013).

considerably, while it becomes zero in the normalized case. Interestingly, the percentages of articles in the intersections $X \cap B'$, and $X \cap Y'$ remain essentially the same as before.

Table 3 around here

2. In the second place, Figure 2.A shows a histogram of the distribution of the proportion of high-impact articles in B and Y over the 5,119 clusters. As expected, the distribution of these proportions for set B is way off the mark. The percentage of articles in cluster j in the interval [0.09, 0.11], with a 10% deviation from the proportion 0.10, takes place in only 282 of the 5,119 clusters, and includes 8.3% of all high-impact articles. After normalization, although these magnitudes increase to 2,244 clusters and a percentage of 56.1% articles, they are still not very large. Furthermore, an inspection of the tails of the Y histogram in Figure 2.B indicates that, for many clusters, the percentage of articles in Y_j is not included in the interval [0.05, 0.145). Clearly, even allowing for random variation, the impact of the standard field-normalization procedure is far from perfect. In other words, the universality condition is not satisfied. Finally, when we restrict the attention to the 3,332 clusters with more than 250 publications, Figure 2.C illustrates the greater concentration of clusters towards the 10% percentage. After normalization, 1,829 clusters including 57.6% of the total articles are included in the interval [0.09, 0.11].

Figure 2 around here

In brief, although the standard field-normalization procedure works well for the 3,332 clusters with more than 250 publications, the universality condition for the 5,119 clusters is not satisfied. This leads to the conclusion that the sets of high-impact articles before and after field-normalization, X and Y, present some differences: approximately 5% of articles in X are not found in Y, and the percentage of articles in a cluster with a 10% deviation from 0.10 takes place in only 1,829 clusters which include 57.6% of the total number of articles.

IV.4. Differences in university rankings under the two solutions to all-sciences aggregation problem

The university rankings with and without normalization according to the top 10% indicator, T_i* and T_i, and according to the average of high-impact gaps, $A*_i$ and A_i, are presented in Table A in the Appendix. Universities are ordered according to the indicator T_i.[9] Recall that, under the fractional approach, the articles assigned to the union of the 500 LR universities represent only 52.1% of the total. Nevertheless, the weighted average of the T_i and T_i* values for these universities, using as weights their relative publication output, is 1.14 and 1.13, respectively. Similarly, these figures for the A_i and A_i* values are 1.18 and 1.16. This indicates that the contribution of these universities is clearly above the world average according to both indicators.

We next arrive to the key empirical question of the paper, namely, the consequences of adopting the two solutions to the all-sciences aggregation problem introduced in Section III.2. We begin with the comparison of university rankings according to T_i and $T*_i$. Both the Pearson and the Spearman correlation coefficients between university values are 0.99. However, high correlations between university values and ranks do not preclude important differences for individual universities. In analyzing the consequences of going from T_i to $T*_i$, we must take two aspects into account. Firstly, we should analyze the re-rankings that take place in such a move. Secondly, we should compare the differences between the university values themselves.[10] Fortunately, we have a relevant instance with which to compare our results: the differences found in Ruiz-Castillo & Waltman (2015) in going from

[9] This is also the Top 10% indicator computed in Ruiz-Castillo & Waltman (2015). Minor differences between the two rankings are due to rounded errors (Compare the ranking under classification system 8 in Table C in the Appendix in the working paper version of Ruiz-Castillo & Waltman –http://hdl.handle.net/10016/18385– with the ranking in column 3 in Table A in the Appendix to this paper).

[10] As pointed out by Waltman *et al.* (2012b), since university value distributions are somewhat skewed, an increase in the rank of a university by, say, 10 positions is much more significant in the top of the ranking than further down the list. Therefore, a statement such as "University *u* is performing 20% better than university *v* according to the top 10% indicator" is more informative than a statement such as "University *u* is ranked 20 positions higher than university *v* according to the top 10% indicator."

the university rankings according to T_i using the Web of Science classification system with 236 journal subject categories, or sub-fields, and the classification system we are using in this paper with 5,119 clusters. The results for both situations are in Table 4.

Table 4 around here

As much as 37.2% of universities experience very small re-rankings of less than or equal to five positions, while 70 universities, or 14.0% of the total, experience re-rankings greater than 25 positions. These figures are 20.2% and 39.0% when going from the WoS classification system to our dataset. Among the first 100 universities, 60 experience small re-rankings in going from T_i to T^*_i, while only 44 are in this situation in the change between classification systems. As far as the cardinal changes is concerned, 82.8% of universities have changes in top 10% indicator values smaller than or equal to 0.05 when going from T_i to T^*_i. This percentage is 71% among the first 100 universities. These figures are 50.1% and 60.0% in the change between classification systems. For most universities, the differences are more or less negligible. Although for some universities more significant differences can be observed, the conclusion is clear. The differences observed in university rankings according to the top 10% indicator when we adopt the two solutions for solving the all-sciences aggregation problem are considerably fewer than according to the same indicator when we move from the WoS classification system to our dataset.

The results for the comparison between university rankings according to the average of high-impact gaps are in Table 5. Although a systematic comparison between the indicators T_i and A_i is beyond the scope of this paper, by comparing the corresponding rankings in Table A in the Appendix the following three points are worth emphasizing. Firstly, the lack of robustness of A_i to extreme observations is very apparent. The following universities gain a large number of positions (in brackets) due to the impact of highly-cited articles: University of Göttingen (264), the University of Florida (202), Lund University (191), Osaka University (318), and Tohoku University (311). In the ranking according to T_i, these universities occupy positions 265, 248, 281, 397, and 407, respectively.[11] Secondly, because the high-impact articles of certain universities receive citations close to the CCLs, they do lose positions (in brackets) when we move from T_i to A_i. This is the case, for example, of University of Texas-SW Medical Center (loosing 282 positions), London School of Hygiene and Tropical Medicine (216), Lancaster University (224), University of Exeter (2017), and Paris École Politechnique (208). In the ranking according to T_i, these universities occupy positions 10, 13, 77, 91, and 95, respectively. Thirdly, the range of variation and the inequality exhibited by A_i values are considerably greater than those exhibited by the T_i values. For example, the coefficients of variation for the A_i and the T_i values are 1.36 and 0.35. Thus, there is no doubt that both indicators generate considerably different university rankings. Consequently, it is important to examine the consequences of adopting the two solutions to the all-sciences aggregation problem using the average of high-impact gaps indicator.

Table 5 around here

The Pearson correlation coefficient between the A_i and A^*_i university values is 0.48, while the Spearman correlation coefficient between ranks is 0.99. However, the low Pearson correlation coefficient is due to the presence of the University of Göttingen. Without this university, this correlation coefficient becomes 0.99. In any case, as before, high correlations between university values and ranks do not preclude important differences for individual universities. The ordinal differences in university rankings according to this indicator with and without field-normalization are much smaller than those obtained with the top 10% indicator. For example, 66.6% of universities experience very small re-rankings of less than or equal to five positions, while 20 universities, or 4.0% of the total,

[11] We note that the University of Göttingen is quite a special case. The Mean Normalized Citation Score, and hence the A_i value of the University of Göttingen is known to be strongly determined by a single extremely highly cited publication (see Waltman *et al.*, 2012b, for more details on this case).

experience re-rankings greater than 16 positions. Among the first 100 universities, 78 experience small re-rankings in going from A_i to A^*_i (in comparison with 60 when going from T_i to T^*_i).

As far as the cardinal changes are concerned, we should recall the high coefficient of variation of the 500 A_i values, equal to 1.36. However, normalization radically changes the situation: the range of variation and the coefficient of variation of the A^*_i values are now much smaller than before (see Table A). Consequently, the cardinal changes between A_i to A^*_i are much larger than between T_i to T^*_i: 41.8% of universities have changes in indicator values smaller than or equal to 0.05 when going from A_i to A^*_i –in comparison to 82.8% when going from T_i to T^*_i.

V. CONCLUSIONS

The heterogeneity of the fields distinguished in any classification system poses a grave aggregation problem when one is interested in evaluating the citation impact of a set of research units in the all-sciences case. In this paper, we have analyzed two possible solutions to this problem. The first solution relies on prior normalization of the raw citations received by all publications. In particular, we focus on the standard field-normalization procedure in which field mean citations are used as normalization factors. The second solution extends the approach adopted in the Leiden and SCImago rankings for computing the Top 10% indicator in the all-sciences case to any admissible indicator. This solution does not require any prior field-normalization: the citation impact of any research unit in the all-sciences case is calculated as the appropriately weighted sum of the citation impact that the unit achieves in each field.

Conceptually, the difference is clear. The usual solution starts by determining the set of high-impact articles in the overall normalized citation distribution for publications in all fields. Given a citation indicator, the key reference for each research unit is the unique normalized number of citations that determines the set of high-impact articles for all sciences taken together. The alternative solution preserves the units' key reference at the level of each individual field. In other words, the difference boils down to the way the set of high-impact articles in the all-sciences case is constructed. In the usual solution, it is built up in a single stroke after normalization. In the alternative solution, it is built up from the set of high-impact articles in each field. In this case, all fields are treated fairly in the sense that each contributes to the overall set of high-impact articles in the same proportion to its size.

In practice, the more field citation distributions differ only by a scale factor, the better will be the performance of the standard field-normalization procedure in eliminating the effect of differences between field on overall citation inequality, the more the two sets of high-impact articles will resemble each other, and the smaller will be the difference between the two approaches independently of the citation impact indicator we care to use in the evaluation of the research units.

Using a large WoS dataset consisting of 3.6 million publications in the 2005-2008 period and an algorithmically constructed publication-level classification system that distinguishes between 5,119 clusters, the two alternatives have been confronted when the citation impact of the 500 LR universities are evaluated using two indicators with very different properties: the Top 10% indicator, and the Average of high-impact gaps.

The shape of the citation distributions of 4,161 significant clusters with more than 100 publications in our dataset has been previously shown to be highly skewed and reasonably similar (Ruiz-Castillo & Waltman, 2015). Previous results with WoS classification systems that distinguish at most between 235 sub-fields indicate that, when this is the case, the standard field-normalization procedure performs well in reducing the overall citation inequality attributed to the differences in production and citation practices between fields. In this paper, we have shown that when we restrict our attention to 3,332 clusters with more than 250 publications this is also the case. Nevertheless, *a priori* it is not obvious what to expect when we confront the two solutions to the all-sciences aggregation problem with and without prior field-normalization for the 5,119 clusters.

Interestingly enough, the differences between the university rankings obtained with both solutions is of a small order of magnitude independently of the citation impact indicator used in the construction of the university rankings. In particular, these differences are considerably smaller than the ones obtained in Ruiz-Castillo & Waltman (2015) when we move from the WoS classification system with 236 sub-fields to the one used in this paper with 5,119 clusters.

In principle, it seems preferable to evaluate the citation impact of research units in the all-sciences case avoiding any kind of prior normalization operation. However, the empirical evidence we have presented indicates that the method relying on the prior standard field-normalization does not lead to very different results. This is a convenient conclusion, since there are instances when normalization is strongly advisable; for example, when one is interested in studying the research units' citation distributions in the all-sciences case –as we do in the companion paper Perianes-Rodriguez & Ruiz-Castillo (2014).

It should be noted that, before being accepted, it would be advisable to replicate the results of this paper for other datasets, other classification systems, other types of research units, and other ways of assigning responsibility between research units in the case of co-authored publications.

REFERENCES

Albarrán, P., Ortuño, I., & Ruiz-Castillo, J. (2011a). The measurement of low- and high-impact in citation distributions: technical results. *Journal of Informetrics*, *5*, 48–63.

Albarrán, P., Crespo, J., Ortuño, I., & Ruiz-Castillo, J. (2011b). The skewness of science in 219 sub-fields and a number of aggregates. *Scientometrics*, *88*, 385–397.

Bornmann, L., De Moya Anegón, F., Leydesdorff, L. (2012) The new Excellence Indicator in the World Report of the SCImago Institutions Rankings 2011. Journal of Informetrics, *6*, 333-335.

Brzezinski, M. (2015). Power laws in citation distributions: Evidence from Scopus, *Scientometrics*, **103**: 213-228.

Crespo, J. A., Li, Y., & Ruiz-Castillo, J. (2013). The measurement of the effect on citation inequality of differences in citation practices across scientific fields. *PLoS ONE*, *8*, e58727.

Crespo, J. A., Herranz, N., Li, Y., & Ruiz-Castillo, J. (2014). The effect on citation inequality of differences in citation practices at the Web of Science subject category level. *Journal of the American Society for Information Science and Technology*, *65*, 1244–1256.

Groeneveld, R.A., Meeden, G. (1984). Measuring skewness and kurtosis. *The Statistician*, **33**: 391–399.

Li, Y., Castellano, C., Radicchi, F., & Ruiz-Castillo, J. (2013). Quantitative evaluation of alternative field normalization procedures. *Journal of Informetrics*, *7*, 746–755.

Perianes-Rodriguez, A., and Ruiz-Castillo, J. (2014). University citation distributions. Working Paper 14-26, Universidad Carlos III (http://hdl.handle.net/10016/19811).

Radicchi, F., & Castellano, C. (2012). A reverse engineering approach to the suppression of citation biases reveals universal properties of citation distributions. *PLoS ONE*, *7*, e33833.

Radicchi, F., Fortunato, S., and Castellano, C. (2008), "Universality of Citation Distributions: Toward An Objective Measure of Scientific Impact", *PNAS*, **105**: 17268-17272.

Ruiz-Castillo, J. (2014). The comparison of classification-system-based normalization procedures with source normalization alternatives in Waltman and Van Eck. *Journal of Informetrics*, *8*, 25–28.

Ruiz-Castillo, J. & Waltman, L. (2015). Field-normalized citation impact indicators using algorithmically constructed classification systems of science. *Journal of Informetrics*, *9*, 102-117.

Schubert, A., Glänzel, W., & Braun, T. (1987). Subject field characteristic citation scores and scales for assessing research performance. *Scientometrics*, *12*, 267–292.

Thelwall, M., & Wilson, P. (2014), Distributions for cited articles from individual subjects and years. *Journal of Informetrics*, *8*, 824-839.

Waltman, L., & Van Eck, N. J. (2012). A new methodology for constructing a publication-level classification system of science. *Journal of the American Society for Information Science and Technology*, *63*, 2378–2392.

Waltman, L., Calero-Medina, C., Kosten, J., Noyons, E. C. M., Tijssen, R. J. W., Van Eck, N. J., Van Leeuwen, T. N., Van Raan, A. F. J., Visser, M. S., & Wouters, P. (2012a). The Leiden Ranking 2011/2012: Data collection, indicators, and interpretation. *Journal of the American Society for Information Science and Technology*, *63*, 2419–2432.

Waltman, L., Van Eck, N. J., & Van Raan, A. F. J. (2012b). Universality of citation distributions revisited. *Journal of the American Society for Information Science and Technology*, *63*, 72–77.

Waltman, L., and Schreiber, M. (2013). On the calculation of percentile-based bibliometric indicators. *Journal of the American Society for Information Science and Technology*, *64*, 372-379.

Waltman, L., & Van Eck, N. J. (2013). A systematic empirical comparison of different approaches for normalizing citation impact indicators. *Journal of Informetrics*, *7*, 833–849.

APPENDIX

Table A. Number of publications, and citation impact indicators for the 500 Leiden Ranking universities

				Top 10%			Average high-impact gaps			
Rank T	**University**	**Number articles**	**‰**	**T**	**T***	**Rank T***	**A**	**A***	**Rank A**	**Rank A***
1	MIT	8346.96	2.31	2.41	2.45	1	3.46	3.66	4	3
2	Harvard Univ	26869.03	7.43	2.27	2.19	4	3.08	3.09	2	1
3	Princeton Univ	4548.18	1.26	2.22	2.31	2	2.95	3.19	30	26
4	Stanford Univ	11936.96	3.30	2.19	2.19	3	2.78	2.88	3	2
5	Caltech	5264.76	1.46	2.12	2.14	5	3.01	3.13	24	23
6	Univ Calif - Berkeley	9185.55	2.54	2.07	2.09	6	2.64	2.80	9	6
7	Univ Calif - Santa Barbara	4192.33	1.16	1.94	1.98	7	2.58	2.72	40	39
8	Univ Calif - San Francisco	8757.91	2.42	1.93	1.82	9	2.10	2.07	18	17
9	Yale Univ	8673.49	2.40	1.88	1.86	8	2.13	2.18	16	16
10	Univ Texas - SW Med Ctr	1205.78	0.33	1.82	1.71	21	1.75	1.77	292	293
11	Univ Chicago	6133.82	1.70	1.80	1.79	11	2.12	2.22	32	30
12	Univ Washington - Seattle	12522.58	3.46	1.80	1.76	14	2.03	2.06	8	7
13	London Sch Hyg & Trop Med	1275.71	0.35	1.79	1.70	22	2.45	2.38	219	225
14	Univ Calif - San Diego	9989.19	2.76	1.77	1.75	15	2.13	2.14	13	13
15	Ecole Polytech Fédérale Lausanne	3743.56	1.04	1.77	1.79	12	2.12	2.24	61	58
16	Northwestern Univ	8079.59	2.24	1.77	1.78	13	2.03	2.12	23	22
17	Carnegie Mellon Univ	2911.52	0.81	1.76	1.82	10	1.84	2.07	111	98
18	Univ Calif - Los Angeles	13267.10	3.67	1.73	1.71	19	1.98	2.04	5	4
19	Columbia Univ	10665.61	2.95	1.73	1.71	20	1.99	2.04	14	12
20	ETH Zurich	6706.32	1.86	1.73	1.73	17	1.88	2.00	34	31
21	Weizmann Inst Sci	2523.16	0.70	1.73	1.73	18	1.87	1.96	123	121
22	Rice Univ	2082.25	0.58	1.72	1.74	16	1.93	2.07	157	150
23	Univ Penn	11438.51	3.16	1.71	1.66	27	1.84	1.86	15	14
24	Univ Calif - Santa Cruz	1746.33	0.48	1.71	1.66	26	1.87	2.01	203	194
25	Univ Colorado - Boulder	4335.50	1.20	1.70	1.67	24	1.79	1.82	64	63
26	Univ Oxford	10910.70	3.02	1.68	1.66	28	2.07	2.13	11	9
27	Duke Univ	9017.75	2.49	1.68	1.63	29	1.94	1.94	19	19
28	Washington Univ - St Louis	7675.87	2.12	1.65	1.60	32	1.68	1.72	33	32
29	Johns Hopkins Univ	12894.39	3.57	1.63	1.59	34	1.79	1.82	10	8
30	NYU	6363.60	1.76	1.63	1.67	25	1.77	1.90	38	36
31	Georgia Inst Technol	5365.31	1.48	1.62	1.68	23	1.81	1.93	43	41
32	Emory Univ	5732.15	1.59	1.62	1.55	38	1.61	1.61	48	50
33	Univ Cambridge	11145.30	3.08	1.62	1.61	30	2.29	2.03	6	11
34	Cornell Univ	10368.50	2.87	1.60	1.59	33	1.78	1.83	17	15
35	Univ Michigan	14286.46	3.95	1.60	1.59	35	1.78	1.82	7	5
36	Univ Calif - Riverside	2955.94	0.82	1.58	1.55	37	1.65	1.75	119	116
37	Imperial Coll London	9124.62	2.52	1.58	1.60	31	1.67	1.74	25	24
38	Dartmouth Coll	1959.29	0.54	1.58	1.57	36	1.65	1.70	207	205
39	Boston Univ	5410.13	1.50	1.56	1.53	43	1.66	1.68	51	52
40	Tufts Univ	3334.42	0.92	1.56	1.52	44	1.67	1.68	105	108
41	Univ Coll London	10137.88	2.80	1.55	1.53	41	1.71	1.73	20	18
42	Univ Calif - Irvine	5614.27	1.55	1.54	1.54	39	1.60	1.65	52	49
43	Icahn Sch Med Mt Sinai	2940.92	0.81	1.53	1.44	52	1.53	1.50	136	144
44	Baylor Coll Med	4743.18	1.31	1.53	1.46	51	1.47	1.45	75	80
45	Univ N Carolina - Chapel Hill	8073.43	2.23	1.52	1.49	47	1.73	1.74	28	28
46	Vanderbilt Univ	6160.79	1.70	1.50	1.46	50	1.40	1.41	55	56
47	Univ Illinois-Urbana-Champaign	8957.90	2.48	1.50	1.53	40	1.63	1.72	26	25
48	Univ Texas - Austin	6915.13	1.91	1.50	1.53	42	1.54	1.66	41	38
49	Univ Wisconsin - Madison	11122.78	3.08	1.50	1.48	48	1.51	1.55	21	20
50	Univ Bristol	5214.85	1.44	1.48	1.47	49	1.58	1.62	58	57
51	Univ Maryland - College Park	5750.50	1.59	1.48	1.52	45	1.53	1.62	53	48

Rank T	University	Number articles	‰	Top 10% T	T*	Rank T*	Average high-impact gaps A	A*	Rank A	Rank A*
52	Univ Lausanne	2681.10	0.74	1.48	1.40	63	1.68	1.67	137	143
53	Univ Massachusetts Med Sch	1869.97	0.52	1.47	1.42	59	1.51	1.50	233	242
54	Univ Virginia	5362.96	1.48	1.46	1.44	55	1.37	1.40	70	71
55	Univ Edinburgh	5680.62	1.57	1.44	1.41	60	1.41	1.43	59	60
56	Univ Twente	2158.45	0.60	1.44	1.49	46	1.42	1.54	223	207
57	Univ Massachusetts - Amherst	2995.72	0.83	1.44	1.43	56	1.30	1.40	159	155
58	Univ Minnesota - Twin Cities	10591.10	2.93	1.43	1.41	61	1.57	1.63	22	21
59	Univ Pittsburgh	9970.57	2.76	1.42	1.36	72	1.39	1.39	29	29
60	Oregon Hlth & Sci Univ	2107.95	0.58	1.42	1.42	58	1.60	1.60	194	200
61	Univ So Calif	6506.76	1.80	1.42	1.44	54	1.39	1.48	50	45
62	Univ St Andrews	1793.03	0.50	1.42	1.44	53	2.10	2.23	171	165
63	Univ Rochester	4489.99	1.24	1.41	1.41	62	1.53	1.57	80	77
64	Wageningen Univ & Res Ctr	3569.58	0.99	1.41	1.36	74	1.15	1.14	151	159
65	Brown Univ	3875.48	1.07	1.40	1.40	65	1.50	1.55	94	100
66	Univ Basel	3333.66	0.92	1.39	1.31	82	1.34	1.35	139	140
67	Univ Utah	5413.63	1.50	1.39	1.37	69	1.35	1.39	71	70
68	Univ Zurich	5635.53	1.56	1.39	1.35	75	1.27	1.30	72	74
69	Tech Univ Denmark	3407.99	0.94	1.38	1.37	70	1.25	1.33	146	139
70	Durham Univ	2447.57	0.68	1.37	1.38	67	1.30	1.37	217	203
71	Erasmus Univ Rotterdam	5117.32	1.42	1.37	1.32	81	1.32	1.31	81	82
72	Univ Dublin Trinity Coll	2034.74	0.56	1.36	1.33	77	1.77	1.83	180	178
73	Univ Dundee	1938.12	0.54	1.36	1.31	83	1.98	1.98	163	172
74	King's Coll London	4978.33	1.38	1.35	1.31	86	1.38	1.40	78	79
75	Delft Univ Technol	3425.51	0.95	1.35	1.40	64	1.67	1.77	101	96
76	Univ Toronto	16286.58	4.51	1.35	1.32	80	1.36	1.39	12	10
77	Lancaster Univ	1474.69	0.41	1.35	1.43	57	1.33	1.39	301	301
78	Univ Colorado - Denver	3967.30	1.10	1.35	1.27	101	1.29	1.26	114	119
79	Leiden Univ	4892.52	1.35	1.35	1.30	88	1.23	1.24	92	97
80	Stony Brook Univ - SUNY	3288.95	0.91	1.34	1.35	76	1.36	1.43	140	133
81	Univ Calif - Davis	9626.67	2.66	1.34	1.36	73	1.28	1.32	36	35
82	Penn State Univ	9558.66	2.64	1.34	1.37	71	1.48	1.50	27	27
83	Tech Univ München	4682.16	1.30	1.34	1.30	92	1.29	1.36	91	86
84	Univ Cincinnati	4893.64	1.35	1.33	1.30	89	1.17	1.16	100	106
85	Yeshiva Univ	2914.80	0.81	1.33	1.28	96	1.34	1.32	160	173
86	Univ York	2577.90	0.71	1.33	1.31	87	1.24	1.24	216	213
87	Univ Amsterdam	6335.52	1.75	1.32	1.29	93	1.26	1.28	60	61
88	Rutgers State Univ	4405.15	1.22	1.31	1.38	68	1.40	1.48	88	84
89	Univ East Anglia	1613.78	0.45	1.31	1.29	94	1.54	1.55	264	269
90	VU Univ Amsterdam	5189.56	1.44	1.30	1.27	99	1.20	1.20	86	90
91	Univ Exeter	1619.95	0.45	1.30	1.31	85	1.21	1.24	298	304
92	Univ British Columbia	9776.64	2.70	1.30	1.30	90	1.27	1.31	35	34
93	Indiana Univ - Bloomington	3223.43	0.89	1.29	1.30	91	1.17	1.25	168	163
94	Utrecht Univ	7463.78	2.06	1.29	1.27	100	1.22	1.20	49	54
95	ParisTech - École Polytech	1294.38	0.36	1.28	1.39	66	1.50	1.67	303	292
96	Univ Geneva	3944.62	1.09	1.28	1.28	98	1.44	1.49	102	102
97	Univ Notre Dame	2130.68	0.59	1.28	1.31	84	1.44	1.55	222	209
98	Arizona State Univ	4378.27	1.21	1.27	1.29	95	1.95	1.77	57	66
99	Univ Iowa	5750.55	1.59	1.27	1.27	102	1.10	1.17	84	81
100	Georgetown Univ	2276.93	0.63	1.27	1.24	109	1.15	1.19	251	246
101	Katholieke Univ Leuven	8495.16	2.35	1.26	1.26	105	1.31	1.33	39	40
102	Australian Natl Univ	4177.73	1.16	1.26	1.28	97	1.32	1.36	106	105
103	Case Western Reserve Univ	5210.05	1.44	1.26	1.23	111	1.21	1.21	85	87
104	Eindhoven Univ Technol	2737.82	0.76	1.25	1.33	78	1.22	1.37	195	177
105	Oregon State Univ	3112.90	0.86	1.25	1.19	132	1.25	1.29	161	164
106	Univ Sheffield	5146.75	1.42	1.25	1.26	103	1.17	1.20	93	92

				Top 10%			Average high-impact gaps			
Rank T	University	Number articles	‰	T	T*	Rank T*	A	A*	Rank A	Rank A*
107	Michigan State Univ	5923.03	1.64	1.24	1.25	106	1.16	1.21	77	76
108	Ohio State Univ	9339.35	2.58	1.24	1.24	108	1.22	1.27	37	37
109	Univ Aberdeen	2700.20	0.75	1.24	1.20	121	1.21	1.16	201	221
110	Aarhus Univ	5391.13	1.49	1.23	1.18	136	1.08	1.08	95	103
111	Maximilians-Univ München	6362.39	1.76	1.23	1.19	130	1.22	1.22	65	65
112	Univ Glasgow	4220.41	1.17	1.23	1.20	122	1.27	1.30	109	111
113	Univ Texas-Hlth Sci Ctr S Antonio	602.85	0.17	1.23	1.16	143	1.02	1.00	463	469
114	Univ Melbourne	7278.97	2.01	1.23	1.22	113	1.28	1.31	47	46
115	Univ Copenhagen	7764.57	2.15	1.23	1.19	133	1.24	1.22	44	47
116	Paris Diderot Univ	2662.09	0.74	1.22	1.23	112	1.25	1.32	196	190
117	Univ Stuttgart	2209.05	0.61	1.22	1.33	79	1.49	1.62	198	187
118	Univ Freiburg	3719.61	1.03	1.22	1.20	125	1.09	1.12	156	156
119	Univ Nice Sophia Antipolis	1237.69	0.34	1.22	1.19	129	1.16	1.20	359	358
120	Univ Arizona	6434.62	1.78	1.21	1.21	118	1.23	1.27	62	59
121	Univ Würzburg	3200.89	0.89	1.21	1.18	134	0.97	0.98	220	220
122	McMaster Univ	4991.50	1.38	1.21	1.22	114	1.48	1.48	69	72
123	Karlsruhe Inst Technol	3593.14	0.99	1.21	1.26	104	1.28	1.36	133	122
124	Univ Bern	3640.74	1.01	1.20	1.17	139	1.34	1.32	118	130
125	Northeastern Univ	1355.63	0.38	1.20	1.21	119	1.27	1.36	330	320
126	Univ New Mexico	2779.78	0.77	1.20	1.20	126	1.25	1.34	185	179
127	Paris Descartes Univ	2831.72	0.78	1.19	1.15	148	1.14	1.13	208	216
128	McGill Univ	8491.34	2.35	1.19	1.17	140	1.16	1.18	42	42
129	Univ Paris-Sud 11	4559.22	1.26	1.19	1.23	110	1.26	1.33	99	95
130	Univ Southampton	4746.28	1.31	1.19	1.22	115	1.31	1.32	87	88
131	Wake Forest Univ	2580.47	0.71	1.19	1.14	155	1.16	1.15	224	228
132	Hong Kong Univ Sci & Technol	2835.54	0.78	1.19	1.24	107	0.94	1.05	246	229
133	Univ Nottingham	5269.36	1.46	1.19	1.20	128	1.03	1.07	108	107
134	Univ Delaware	2833.87	0.78	1.18	1.20	120	1.04	1.08	228	224
135	Univ Queensland	6715.11	1.86	1.18	1.15	146	1.13	1.13	67	69
136	Univ Maryland - Baltimore	3614.61	1.00	1.18	1.14	151	1.01	0.99	177	185
137	Univ Paris-Est Créteil	884.33	0.24	1.18	1.20	127	0.92	0.96	436	433
138	Univ Pierre & Marie Curie	6652.52	1.84	1.18	1.19	131	1.04	1.09	76	75
139	Univ Groningen	5405.11	1.50	1.17	1.16	144	1.05	1.06	104	104
140	Tulane Univ	1784.64	0.49	1.17	1.13	160	1.16	1.15	294	299
141	Purdue Univ - Lafayette	6619.30	1.83	1.17	1.21	116	1.08	1.16	73	67
142	Univ Warwick	2613.84	0.72	1.17	1.20	123	1.06	1.10	239	235
143	Florida State Univ	3068.63	0.85	1.17	1.20	124	1.24	1.28	166	166
144	Stockholm Univ	2613.92	0.72	1.17	1.17	141	1.23	1.22	209	217
145	Univ Bath	1846.12	0.51	1.16	1.21	117	1.00	1.07	310	305
146	Univ Libre Bruxelles	2498.57	0.69	1.16	1.14	153	1.12	1.16	235	232
147	Univ S Carolina	2539.80	0.70	1.16	1.17	138	0.99	1.02	261	259
148	Univ Erlangen-Nürnberg	4032.16	1.12	1.15	1.14	154	1.16	1.18	125	131
149	Colorado State Univ	3335.54	0.92	1.15	1.12	164	1.06	1.04	181	195
150	Univ Miami - Miami	4026.15	1.11	1.15	1.12	166	1.18	1.20	122	127
151	Univ Liverpool	3778.52	1.05	1.15	1.14	157	1.02	1.02	162	170
152	Karolinska Inst	6896.32	1.91	1.14	1.08	190	1.14	1.11	63	68
153	Radboud Univ Nijmegen	4905.54	1.36	1.14	1.12	165	1.06	1.07	113	113
154	Univ Hawaii - Manoa	2743.27	0.76	1.14	1.14	152	1.08	1.06	227	233
155	Univ Leeds	5133.15	1.42	1.14	1.13	158	1.05	1.07	110	110
156	Univ Bonn	3884.12	1.07	1.14	1.14	150	1.08	1.09	148	153
157	Univ Reading	1947.91	0.54	1.13	1.11	168	1.09	1.09	290	294
158	Goethe Univ Frankfurt	3533.21	0.98	1.13	1.11	171	1.07	1.09	167	174
159	Univ Catholique Louvain	2863.32	0.79	1.13	1.12	162	0.95	0.96	242	245
160	Newcastle Univ	3562.16	0.99	1.13	1.14	156	1.06	1.08	169	175
161	Monash Univ	4901.90	1.36	1.12	1.11	170	0.98	1.03	121	118

Rank T	University	Number articles	‰	Top 10% T	T*	Rank T*	Average high-impact gaps A	A*	Rank A	Rank A*
162	Univ Ottawa	3757.38	1.04	1.12	1.11	177	1.01	1.03	165	168
163	Univ Bordeaux Segalen	1433.67	0.40	1.12	1.11	175	1.14	1.14	334	341
164	Tech Univ Berlin	1842.14	0.51	1.12	1.18	137	0.99	1.05	314	311
165	Humboldt-Univ Berlin	4797.29	1.33	1.12	1.09	183	0.97	0.97	128	134
166	RWTH Aachen University	3596.67	1.00	1.12	1.13	159	1.12	1.35	155	126
167	Natl Univ Singapore	9155.48	2.53	1.12	1.16	145	1.04	1.08	45	43
168	Univ Cent Florida	2153.04	0.60	1.11	1.15	149	0.98	1.09	293	278
169	Univ Montpellier 2	2116.08	0.59	1.11	1.13	161	1.28	1.27	243	249
170	Queen Mary Univ London	1824.78	0.50	1.11	1.15	147	1.07	1.33	302	273
171	Univ Georgia	4498.92	1.24	1.11	1.11	174	1.02	1.03	130	136
172	Univ New S Wales	5188.44	1.44	1.10	1.08	194	1.06	1.07	107	109
173	Vienna Univ Technol	1616.49	0.45	1.10	1.18	135	1.00	1.11	335	327
174	Univ Sydney	7448.84	2.06	1.10	1.09	184	1.02	1.05	66	64
175	Joseph Fourier Univ	2803.90	0.78	1.10	1.11	176	1.10	1.15	221	210
176	Univ Vermont	1836.31	0.51	1.10	1.04	221	1.01	1.02	309	318
177	Univ Sussex	1633.70	0.45	1.10	1.08	188	1.08	1.11	319	324
178	Univ Strasbourg	3101.51	0.86	1.09	1.07	195	1.14	1.15	182	186
179	Philipps-Univ Marburg	2314.61	0.64	1.09	1.08	192	1.02	1.05	271	275
180	Univ Manchester	8213.38	2.27	1.09	1.08	189	1.05	1.09	54	53
181	Univ Connecticut	4514.39	1.25	1.09	1.09	185	1.00	1.02	138	137
182	Queen's Univ	3175.83	0.88	1.09	1.07	198	1.01	1.04	210	208
183	Gutenberg Univ Mainz	2956.67	0.82	1.09	1.04	212	1.10	1.13	206	204
184	Univ Vienna	3345.83	0.93	1.09	1.11	169	1.04	1.09	187	184
185	George Washington Univ	2055.04	0.57	1.08	1.07	196	1.29	1.28	248	252
186	Univ S Florida - Tampa	2985.63	0.83	1.08	1.03	223	1.06	1.07	218	215
187	Norwegian Univ Sci & Technol	2870.02	0.79	1.08	1.10	178	0.97	1.02	236	230
188	Paul Sabatier Univ	3658.61	1.01	1.08	1.08	193	0.88	0.92	212	202
189	Med Coll Wisconsin	2040.48	0.56	1.08	1.03	226	0.81	0.81	333	339
190	Tech Univ Dresden	2965.39	0.82	1.08	1.09	186	0.91	0.95	244	240
191	Univ Auckland	3238.11	0.90	1.08	1.04	213	1.25	1.25	154	161
192	Maastricht Univ	3283.21	0.91	1.08	1.02	234	0.98	0.98	211	214
193	Iowa State Univ	4560.00	1.26	1.08	1.07	199	1.12	1.14	116	115
194	Univ Alabama - Birmingham	4577.52	1.27	1.08	1.03	224	0.93	0.92	145	152
195	Univ Hong Kong	5420.80	1.50	1.08	1.06	201	1.07	1.11	97	99
196	Texas A&M Univ - College Stn	7195.10	1.99	1.07	1.11	172	1.04	1.11	68	62
197	Univ Alberta	7628.39	2.11	1.07	1.06	206	0.93	0.97	74	73
198	Univ Antwerp	2401.88	0.66	1.07	1.01	243	0.96	0.97	275	281
199	Chalmers Univ Technol	1566.22	0.43	1.07	1.12	163	0.90	0.93	363	363
200	Univ Helsinki	6245.52	1.73	1.07	1.03	228	1.03	1.03	83	85
201	Univ Tübingen	4266.29	1.18	1.07	1.06	204	1.01	1.03	143	147
202	Univ Hamburg	3483.39	0.96	1.07	1.06	203	1.08	1.10	172	171
203	Indiana Univ - Purdue	3635.88	1.01	1.07	1.05	210	0.88	0.88	213	212
204	Med Univ S Carolina	2325.95	0.64	1.07	1.02	235	0.95	0.91	283	295
205	Freie Univ Berlin	4558.56	1.26	1.06	1.03	229	0.94	0.95	144	148
206	Univ Otago	2612.83	0.72	1.06	1.01	245	0.97	0.97	259	263
207	Ruhr-Univ Bochum	3125.60	0.86	1.06	1.07	200	0.89	0.96	237	226
208	Drexel Univ	1900.92	0.53	1.06	1.05	208	1.23	1.30	272	272
209	George Mason Univ	1240.82	0.34	1.06	1.12	167	0.96	1.05	391	382
210	Washington State Univ	2964.18	0.82	1.06	1.03	227	0.89	0.90	250	248
211	Univ Regensburg	2477.43	0.69	1.06	1.03	225	0.93	0.95	276	279
212	Univ Duisburg-Essen	2658.14	0.74	1.06	1.09	187	0.94	0.98	262	256
213	Heidelberg Univ	5913.33	1.64	1.05	1.01	249	1.04	1.06	89	89
214	Univ Med & Dent New Jersey	2991.39	0.83	1.05	0.98	267	0.86	0.84	256	266
215	Univ Birmingham	5136.70	1.42	1.05	1.05	211	0.94	0.94	120	128
216	City Univ Hong Kong	3019.82	0.84	1.05	1.17	142	0.91	1.04	240	219

					Top 10%		Average high-impact gaps			
Rank T	University	Number articles	‰	T	T*	Rank T*	A	A*	Rank A	Rank A*
217	Univ Claude Bernard Lyon 1	3552.70	0.98	1.04	1.04	214	1.02	1.03	178	182
218	Univ Bordeaux 1 Sci Technol	1952.95	0.54	1.04	1.10	179	1.12	1.17	285	283
219	Univ Illinois - Chicago	5035.22	1.39	1.04	1.02	240	0.91	0.94	132	132
220	Virginia Tech	3927.56	1.09	1.04	1.07	197	0.83	0.89	205	196
221	Univ Leicester	2598.36	0.72	1.04	1.04	217	0.96	0.96	263	270
222	Simon Fraser Univ	2112.25	0.58	1.04	1.08	191	0.93	0.97	299	300
223	Vrije Univ Brussel	1865.96	0.52	1.04	1.05	207	1.09	1.10	296	302
224	Univ Waterloo	3919.29	1.08	1.04	1.09	182	0.86	0.95	193	180
225	Univ Western Australia	3704.24	1.02	1.04	1.04	220	0.94	0.95	186	193
226	Pohang Univ Sci & Technol	2413.93	0.67	1.03	1.09	181	0.89	0.97	289	280
227	Univ Texas - Medical Branch	2375.57	0.66	1.03	0.93	298	0.83	0.81	300	313
228	Kiel Univ	2668.93	0.74	1.03	1.00	252	0.95	0.95	260	262
229	Virginia Commonwealth Univ	2806.93	0.78	1.03	0.98	264	1.06	1.07	225	227
230	N Carolina State Univ	4878.51	1.35	1.03	1.06	205	0.94	1.00	134	124
231	Heinrich Heine Univ Düsseldorf	2475.67	0.68	1.03	1.04	218	0.91	0.91	279	286
232	Univ Wollongong	1539.76	0.43	1.03	1.04	222	0.93	0.93	361	365
233	Univ Houston - Houston	2049.09	0.57	1.03	1.10	180	0.86	0.94	321	312
234	Ghent Univ	6671.61	1.85	1.03	1.02	238	0.97	0.98	82	83
235	Umeå Univ	2446.22	0.68	1.03	0.99	260	0.87	0.85	291	297
236	Tech Univ Darmstadt	2002.49	0.55	1.02	1.11	173	0.99	1.05	297	296
237	Univ Western Ontario	4647.50	1.29	1.02	1.01	244	0.90	0.91	147	151
238	Univ Calgary	5128.09	1.42	1.02	1.00	255	0.92	0.91	126	135
239	Thomas Jefferson Univ	2122.06	0.59	1.02	0.95	283	0.81	0.79	328	338
240	Giessen Univ	2026.49	0.56	1.02	1.02	239	0.94	0.96	305	307
241	Cardiff University	3524.37	0.98	1.02	0.98	266	0.90	0.90	215	218
242	Hebrew Univ Jerusalem	5596.68	1.55	1.02	1.01	241	0.91	0.94	115	114
243	Wayne State Univ	3789.40	1.05	1.02	1.00	254	0.89	0.89	192	201
244	Univ Montréal	4790.26	1.33	1.02	0.97	277	0.92	0.95	141	138
245	Swed Univ Agr Sci	1835.09	0.51	1.02	0.97	278	0.88	0.85	337	349
246	Univ Bergen	2522.70	0.70	1.01	0.99	258	1.16	1.14	229	236
247	Univ Oslo	5235.41	1.45	1.01	1.00	250	0.86	0.86	135	142
248	Univ Florida	10499.54	2.90	1.01	1.01	248	0.89	0.92	46	44
249	Univ Nebraska - Lincoln	2950.05	0.82	1.01	1.02	232	0.83	0.88	266	258
250	Univ Adelaide	2974.96	0.82	1.01	1.03	231	0.86	0.87	257	260
251	Univ Coll Cork	1713.44	0.47	1.01	1.02	236	0.87	0.87	352	357
252	Med Univ Wien	2991.29	0.83	1.01	0.98	271	0.94	0.95	234	237
253	Dalhousie Univ	3036.58	0.84	1.01	1.01	247	0.84	0.83	258	264
254	Univ Cologne	2958.50	0.82	1.01	0.98	263	0.93	0.96	238	239
255	Aix-Marseille Univ	3429.38	0.95	1.00	1.02	233	0.99	1.03	190	189
256	Univ Münster	3760.00	1.04	1.00	0.98	270	0.88	0.90	197	198
257	Univ Barcelona	5557.79	1.54	1.00	0.97	280	0.94	0.95	112	112
258	Hannover Med Sch	1752.36	0.48	1.00	0.96	282	0.88	0.87	345	353
259	Univ Cape Town	1970.33	0.55	1.00	0.98	265	0.93	0.91	311	326
260	Laval Univ	3613.59	1.00	0.99	0.97	279	0.91	0.89	199	211
261	Friedrich Schiller Univ Jena	2689.34	0.74	0.99	1.00	251	0.89	0.94	269	265
262	Uppsala Univ	4912.01	1.36	0.99	0.98	268	0.94	0.92	129	141
263	Univ Milan Bicocca	816.58	0.23	0.99	1.01	242	0.92	0.96	445	447
264	Montpellier 1 Univ	1092.57	0.30	0.99	0.93	301	0.91	0.89	409	419
265	Univ Göttingen	3646.82	1.01	0.99	0.99	256	29.50	2.52	1	51
266	Univ Bremen	1311.99	0.36	0.98	0.97	273	0.91	0.96	390	387
267	Univ Victoria	1796.94	0.50	0.98	1.02	237	0.80	0.84	360	356
268	Univ Tennessee - Knoxville	4345.57	1.20	0.98	0.99	261	0.96	0.99	150	149
269	Univ Coll Dublin	2762.65	0.76	0.98	0.98	269	0.99	0.95	241	253
270	Univ Politècnica València	2225.83	0.62	0.98	1.04	216	1.05	1.15	274	261
271	Univ Newcastle	1531.94	0.42	0.98	1.04	219	0.83	0.88	378	376

				Top 10%			Average high-impact gaps			
Rank T	University	Number articles	‰	T	T*	Rank T*	A	A*	Rank A	Rank A*
272	Univ Rennes 1	1992.84	0.55	0.98	0.97	272	0.88	0.91	322	323
273	Kansas State Univ	2080.58	0.58	0.98	0.99	257	0.71	0.78	354	342
274	Univ Southern Denmark	1838.70	0.51	0.97	0.93	299	0.96	0.94	320	333
275	York Univ	1608.15	0.44	0.97	1.01	246	0.79	0.79	377	386
276	Univ Buffalo - SUNY	3710.76	1.03	0.97	0.95	284	0.88	0.90	202	206
277	Politecnico Milano	2087.17	0.58	0.97	1.05	209	0.84	0.94	324	306
278	Macquarie Univ	1329.52	0.37	0.96	0.97	276	0.83	0.85	395	396
279	Politecnico Torino	1644.47	0.45	0.96	1.04	215	0.78	0.90	372	361
280	Univ Liège	2333.77	0.65	0.96	0.94	290	0.95	0.95	282	290
281	Lund Univ	6825.63	1.89	0.96	0.93	302	0.89	0.90	90	93
282	Univ Trieste	1215.86	0.34	0.96	0.97	274	1.00	1.03	385	388
283	Univ Politècnica Catalunya	1711.72	0.47	0.95	1.06	202	0.75	1.02	376	331
284	Univ Gothenburg	4200.61	1.16	0.95	0.92	307	0.97	0.96	152	162
285	Univ Rostock	1682.14	0.47	0.95	0.95	289	0.80	0.77	368	381
286	Aalto Univ	2101.97	0.58	0.95	1.03	230	0.90	1.03	307	291
287	Univ Guelph	2846.21	0.79	0.95	0.89	323	0.80	0.72	277	303
288	Indian Inst Technol Madras	1925.53	0.53	0.94	1.00	253	0.51	0.57	411	405
289	Univ Surrey	1866.53	0.52	0.94	0.99	262	0.67	0.74	380	371
290	Univ Louisville	2419.72	0.67	0.93	0.88	326	0.73	0.71	323	334
291	Univ Torino	3402.62	0.94	0.93	0.89	325	0.76	0.76	255	257
292	Loughborough Univ	1941.07	0.54	0.93	0.97	275	0.72	0.76	365	359
293	Univ Seville	2243.73	0.62	0.93	0.93	300	0.69	0.72	348	344
294	Univ Padova	5022.96	1.39	0.92	0.95	287	0.81	0.87	153	146
295	Univ Sci & Technol China	4833.61	1.34	0.92	0.94	294	0.59	0.64	232	223
296	Innsbruck Med Univ	1506.73	0.42	0.92	0.87	334	0.72	0.73	396	404
297	KTH Royal Inst Technol	3135.04	0.87	0.92	0.95	285	0.72	0.77	278	274
298	Univ Kansas	3321.66	0.92	0.92	0.92	305	1.02	1.02	191	197
299	Chinese Univ Hong Kong	4652.17	1.29	0.92	0.94	292	0.78	0.78	179	183
300	Univ Autónoma Barcelona	4139.07	1.15	0.92	0.89	321	0.85	0.86	183	188
301	Univ Milan	6081.82	1.68	0.92	0.93	297	0.82	0.82	117	120
302	Queen's Univ Belfast	2740.36	0.76	0.92	0.94	295	0.85	0.88	273	277
303	Univ Oklahoma	3060.20	0.85	0.91	0.90	317	0.73	0.74	280	285
304	Nanyang Technol Univ	5578.52	1.54	0.91	0.99	259	0.84	0.90	127	117
305	Queensland Univ Technol	1427.76	0.40	0.91	0.93	303	0.73	0.74	403	408
306	Univ Kentucky	4689.97	1.30	0.91	0.90	313	0.79	0.81	176	176
307	Clemson Univ	1873.07	0.52	0.91	0.96	281	0.69	0.73	373	372
308	Temple Univ	2038.64	0.56	0.90	0.89	319	0.76	0.77	347	348
309	Univ Ulm	2325.42	0.64	0.90	0.91	309	0.79	0.80	312	319
310	Univ Strathclyde Glasgow	1825.40	0.51	0.90	0.93	296	0.93	0.97	332	328
311	Univ Nova Lisboa	1290.32	0.36	0.89	0.91	311	0.84	0.84	397	406
312	Univ Missouri - Columbia	4029.19	1.11	0.89	0.91	308	0.85	0.87	189	192
313	Univ Pavia	2082.03	0.58	0.89	0.92	304	0.88	0.94	313	308
314	Univ Tokyo	14623.33	4.05	0.88	0.89	322	0.89	0.90	31	33
315	Henri Poincaré Univ	1804.16	0.50	0.88	0.89	324	0.71	0.74	374	377
316	Univ Leipzig	2915.15	0.81	0.88	0.87	330	0.74	0.76	288	287
317	Univ Zaragoza	2387.33	0.66	0.88	0.94	291	0.75	0.78	315	317
318	Univ Autónoma Madrid	3653.14	1.01	0.87	0.90	315	0.89	0.93	204	199
319	Saarland Univ	1946.71	0.54	0.87	0.86	342	0.74	0.78	358	354
320	Univ Porto	2863.28	0.79	0.87	0.87	333	0.66	0.67	308	314
321	Hunan Univ	1385.93	0.38	0.87	0.95	286	0.52	0.56	450	448
322	Louisiana State Univ	3276.92	0.91	0.86	0.86	338	0.82	0.85	245	243
323	Korea Adv Inst Sci & Technol	3837.45	1.06	0.86	0.92	306	0.69	0.74	249	238
324	Hong Kong Polytech Univ	3539.84	0.98	0.86	0.95	288	0.69	0.74	265	254
325	Univ Tasmania	1279.00	0.35	0.86	0.81	361	0.59	0.56	446	455
326	Guericke Univ Magdeburg	1562.54	0.43	0.86	0.88	327	0.67	0.71	402	401

			Top 10%				Average high-impact gaps			
Rank T	University	Number articles	‰	T	T*	Rank T*	A	A*	Rank A	Rank A*
327	Univ Manitoba	3015.79	0.83	0.86	0.87	337	0.72	0.74	287	288
328	Univ Burgundy	1310.60	0.36	0.86	0.84	349	0.67	0.69	424	426
329	Univ Parma	1740.68	0.48	0.86	0.90	316	0.92	1.00	338	332
330	Univ Florence	3889.85	1.08	0.86	0.83	358	0.75	0.75	230	231
331	Dalian Univ Technol	2792.91	0.77	0.86	0.90	314	0.69	0.74	304	298
332	Peking Univ	6391.90	1.77	0.85	0.86	343	0.74	0.76	124	125
333	Griffith Univ	1453.84	0.40	0.85	0.89	320	0.65	0.63	419	424
334	Technion - Israel Inst Technol	4947.91	1.37	0.85	0.86	340	0.76	0.84	174	157
335	Univ Bologna	5637.18	1.56	0.85	0.87	329	0.74	0.78	149	145
336	Univ Lübeck	1217.29	0.34	0.85	0.80	364	0.68	0.66	435	443
337	Tech Univ Lisbon	2338.12	0.65	0.85	0.94	293	0.73	0.77	331	325
338	Leibniz Univ Hannover	870.33	0.24	0.85	0.90	312	0.83	0.89	451	449
339	Massey Univ	1466.58	0.41	0.85	0.83	357	0.99	0.94	356	370
340	Tel Aviv Univ	6570.61	1.82	0.84	0.86	339	0.70	0.74	131	123
341	S E Univ	1796.21	0.50	0.84	0.83	354	0.99	0.62	316	399
342	Univ Turku	2309.06	0.64	0.84	0.84	352	0.69	0.67	339	351
343	Univ Valencia	3588.41	0.99	0.84	0.84	351	0.68	0.70	268	268
344	Indian Inst Technol Kharagpur	2359.13	0.65	0.84	0.91	310	0.65	0.72	349	335
345	Tsinghua Univ	8361.98	2.31	0.83	0.87	331	0.69	0.74	98	91
346	Univ Mississippi	1708.51	0.47	0.83	0.86	341	0.67	0.69	393	393
347	Sun Yat-sen Univ	3372.93	0.93	0.83	0.83	353	0.65	0.68	284	284
348	Univ Perugia	1804.46	0.50	0.83	0.79	366	0.75	0.77	367	369
349	Lanzhou Univ	2325.14	0.64	0.83	0.87	332	0.64	0.73	353	337
350	Univ Ferrara	1420.57	0.39	0.83	0.83	355	0.99	1.03	364	362
351	Oklahoma State Univ - Stillwater	1523.44	0.42	0.83	0.85	344	0.64	0.71	410	407
352	Stellenbosch Univ	1393.49	0.39	0.81	0.81	360	0.64	0.67	421	422
353	Univ Modena & Reggio Emilia	1610.27	0.45	0.81	0.84	347	0.64	0.68	404	403
354	Natl Tsing Hua Univ	3114.64	0.86	0.81	0.85	346	0.57	0.62	317	310
355	Univ Santiago de Compostela	2618.89	0.72	0.81	0.79	367	0.66	0.70	327	322
356	Auburn Univ	2110.65	0.58	0.81	0.80	363	0.71	0.73	351	352
357	Nankai Univ	2893.01	0.80	0.80	0.88	328	0.60	0.61	329	329
358	Univ Aveiro	1704.12	0.47	0.80	0.85	345	0.63	0.68	400	394
359	Univ Nantes	1398.21	0.39	0.79	0.77	374	0.57	0.59	437	435
360	Univ Basque Country	2287.07	0.63	0.79	0.81	359	0.58	0.61	369	368
361	Aristotle Univ Thessaloniki	4173.94	1.15	0.78	0.81	362	0.53	0.58	281	276
362	Univ Witwatersrand	1457.14	0.40	0.78	0.76	377	0.75	0.76	398	402
363	Amirkabir Univ Technol	936.33	0.26	0.78	0.87	335	0.79	0.84	448	446
364	Sharif Univ Technol	1453.74	0.40	0.78	0.89	318	0.53	0.62	442	428
365	Harbin Inst Technol	3197.93	0.88	0.78	0.84	350	0.90	0.88	231	241
366	Natl Sun Yat-sen Univ	1588.20	0.44	0.78	0.83	356	0.61	0.75	412	392
367	Nanjing Univ	4638.31	1.28	0.77	0.77	373	0.69	0.62	214	234
368	Univ Genoa	2574.46	0.71	0.77	0.77	375	0.84	0.86	286	289
369	Univ Lisbon	1552.95	0.43	0.77	0.75	380	0.55	0.59	430	423
370	Kyoto Univ	11923.46	3.30	0.77	0.78	370	0.72	0.75	56	55
371	Univ Granada	2764.72	0.76	0.76	0.78	371	0.57	0.58	341	343
372	Natl Cent Univ	1666.57	0.46	0.76	0.87	336	0.52	0.59	427	415
373	Univ Napels Federico II	3983.89	1.10	0.76	0.73	389	0.66	0.67	252	251
374	Fudan Univ	5077.27	1.40	0.76	0.75	378	0.59	0.61	226	222
375	Tokyo Med & Dent Univ	1635.61	0.45	0.76	0.75	381	0.54	0.54	426	431
376	Univ Pisa	3734.66	1.03	0.76	0.75	379	0.66	0.67	267	267
377	Bar-Ilan Univ	1735.93	0.48	0.76	0.78	369	0.56	0.58	414	412
378	Univ Eastern Finland	1522.64	0.42	0.76	0.72	394	0.55	0.53	432	442
379	Univ Cattolica Sacro Cuore	1576.32	0.44	0.75	0.73	392	0.57	0.57	422	427
380	Luther Univ Halle-Wittenberg	1811.88	0.50	0.75	0.73	391	0.68	0.68	382	390
381	Pontificia Univ Católica Chile	1169.12	0.32	0.75	0.73	388	0.52	0.54	467	467

				Top 10%			Average high-impact gaps			
Rank T	University	Number articles	‰	T	T*	Rank T*	A	A*	Rank A	Rank A*
382	Wuhan Univ	3323.07	0.92	0.75	0.71	400	0.44	0.46	355	355
383	Univ Patras	2292.87	0.63	0.74	0.73	390	0.56	0.59	375	374
384	Linköping Univ	2393.16	0.66	0.74	0.75	382	0.57	0.59	366	366
385	Univ Oulu	1837.49	0.51	0.74	0.74	383	0.67	0.68	384	389
386	Flinders Univ	1183.11	0.33	0.74	0.70	407	0.47	0.45	471	476
387	Indian Inst Sci	3155.27	0.87	0.74	0.77	376	0.56	0.62	318	309
388	Seoul Natl Univ	9543.91	2.64	0.72	0.72	393	0.59	0.62	103	101
389	Natl Tech Univ Athens	2109.00	0.58	0.72	0.84	348	0.48	0.55	407	395
390	Xiamen Univ	1594.16	0.44	0.72	0.70	408	0.57	0.61	420	418
391	Tokyo Inst Technol	5474.29	1.51	0.71	0.74	387	0.69	0.74	170	160
392	W Virginia Univ	1837.39	0.51	0.71	0.74	385	0.52	0.54	415	414
393	Univ Sains Malaysia	1190.99	0.33	0.71	0.69	411	0.51	0.54	465	463
394	Sapienza Univ Roma	6443.74	1.78	0.71	0.72	398	0.58	0.60	173	169
395	Univ Bari Aldo Moro	2162.83	0.60	0.71	0.70	406	0.56	0.56	387	391
396	Texas Tech Univ	2109.37	0.58	0.71	0.71	401	0.61	0.64	371	375
397	Osaka Univ	9700.65	2.68	0.71	0.71	403	0.71	0.72	79	78
398	Natl Chung Hsing Univ	1889.98	0.52	0.70	0.72	396	0.44	0.47	431	429
399	Univ Oviedo	1895.09	0.52	0.70	0.67	417	0.47	0.48	423	425
400	Natl Taiwan Univ	8402.74	2.32	0.70	0.72	397	0.52	0.57	142	129
401	Univ Roma Tor Vergata	2365.64	0.65	0.70	0.71	402	0.53	0.56	379	378
402	Natl Chiao Tung Univ	3424.93	0.95	0.70	0.79	365	0.46	0.52	342	330
403	Nagoya Univ	5775.65	1.60	0.69	0.70	404	0.60	0.64	184	181
404	Univ KwaZulu-Natal	1122.09	0.31	0.69	0.72	395	0.63	0.75	452	434
405	Shanghai Univ	1621.00	0.45	0.69	0.79	368	0.43	0.48	453	450
406	Shanghai Jiao Tong Univ	7445.41	2.06	0.69	0.74	386	0.50	0.55	175	158
407	Tohoku Univ	9298.67	2.57	0.68	0.70	409	0.62	0.66	96	94
408	Univ Murcia	1613.34	0.45	0.68	0.72	399	0.51	0.53	433	432
409	Middle East Tech Univ	1815.88	0.50	0.68	0.74	384	0.42	0.45	441	438
410	Univ Ulsan	1634.91	0.45	0.66	0.68	416	0.42	0.42	455	458
411	S China Univ Technol	1628.76	0.45	0.66	0.77	372	0.45	0.50	449	439
412	E China Normal Univ	1179.67	0.33	0.66	0.69	410	0.40	0.45	479	478
413	E China Univ Sci & Technol	1752.00	0.48	0.66	0.67	420	0.49	0.55	428	420
414	Complutense Univ	4515.23	1.25	0.66	0.68	413	0.58	0.59	254	250
415	Univ Coimbra	1685.47	0.47	0.65	0.63	429	0.44	0.44	447	452
416	Xi'an Jiaotong Univ	2967.79	0.82	0.65	0.68	412	0.55	0.53	336	347
417	Univ Ljubljana	2890.84	0.80	0.65	0.67	419	0.54	0.55	343	345
418	Zhejiang Univ	9487.91	2.62	0.65	0.65	421	0.42	0.44	158	154
419	Tech Univ Madrid	1597.81	0.44	0.65	0.70	405	0.38	0.42	468	459
420	Shandong Univ	3701.15	1.02	0.64	0.67	418	0.47	0.52	326	315
421	Kyushu Univ	6392.00	1.77	0.64	0.65	422	0.54	0.55	188	191
422	Yonsei Univ	5279.33	1.46	0.64	0.63	427	0.50	0.53	247	244
423	Keio Univ	2988.39	0.83	0.64	0.64	426	0.49	0.49	357	360
424	Univ Warsaw	1823.66	0.50	0.63	0.64	425	1.80	1.49	200	247
425	Natl & Kapodistrian Univ Athens	5454.06	1.51	0.63	0.60	437	0.43	0.45	270	271
426	Ewha Womans Univ	1161.18	0.32	0.63	0.63	430	0.56	0.60	458	457
427	Univ Fed Santa Catarina	1193.53	0.33	0.63	0.64	424	0.32	0.33	488	490
428	Cent S Univ	1856.39	0.51	0.63	0.68	414	0.55	0.61	406	397
429	Jilin Univ	3400.15	0.94	0.62	0.62	433	0.35	0.39	392	379
430	Mahidol Univ	1652.75	0.46	0.62	0.60	441	0.46	0.45	444	451
431	Univ Siena	1817.80	0.50	0.61	0.63	428	0.43	0.44	439	445
432	Natl Cheng Kung Univ	5309.57	1.47	0.61	0.68	415	0.38	0.44	295	282
433	Ben-Gurion Univ Negev	3549.01	0.98	0.60	0.62	435	0.49	0.52	325	321
434	Univ Catania	1745.12	0.48	0.60	0.62	436	0.50	0.51	425	430
435	Univ Saskatchewan	2791.73	0.77	0.59	0.58	446	0.40	0.40	394	398
436	Univ Sci & Technol Beijing	982.50	0.27	0.59	0.64	423	0.36	0.42	489	489

				Top 10%			Average high-impact gaps			
Rank T	University	Number articles	‰	T	T*	Rank T*	A	A*	Rank A	Rank A*
437	Univ Palermo	2178.72	0.60	0.58	0.57	447	0.46	0.47	408	410
438	Tarbiat Modares Univ	934.31	0.26	0.58	0.58	445	0.32	0.30	494	495
439	Korea Univ	3772.21	1.04	0.58	0.59	442	0.42	0.45	344	336
440	Beijing Normal Univ	1524.84	0.42	0.58	0.62	431	0.38	0.40	469	468
441	Cairo Univ	1397.86	0.39	0.57	0.60	438	0.38	0.41	475	472
442	Univ Tsukuba	3415.36	0.94	0.57	0.59	443	0.46	0.48	340	340
443	Chiba Univ	2678.08	0.74	0.57	0.56	450	0.39	0.38	405	411
444	Hanyang Univ	3014.94	0.83	0.57	0.62	434	0.40	0.43	389	380
445	Ege Univ	1860.37	0.51	0.56	0.55	454	0.33	0.34	464	464
446	Kyung Hee Univ	1453.47	0.40	0.56	0.57	448	0.32	0.32	484	483
447	Sungkyunkwan Univ	3842.30	1.06	0.56	0.54	455	0.32	0.33	383	385
448	Tongji Univ	1475.40	0.41	0.56	0.62	432	0.36	0.40	474	470
449	Hiroshima Univ	3488.49	0.97	0.56	0.55	453	0.41	0.41	362	364
450	Tianjin Univ	2692.05	0.74	0.55	0.57	449	0.35	0.35	417	421
451	Sichuan Univ	3612.19	1.00	0.55	0.60	439	0.34	0.38	388	373
452	China Agr Univ	1691.98	0.47	0.55	0.56	452	0.37	0.37	461	466
453	Northwestern Polytech Univ	1208.43	0.33	0.54	0.59	444	0.29	0.35	490	487
454	Hokkaido Univ	6463.48	1.79	0.54	0.54	457	0.40	0.40	253	255
455	Univ Tehran	1986.66	0.55	0.54	0.60	440	0.43	0.42	429	436
456	Chonbuk Natl Univ	1324.51	0.37	0.52	0.56	451	0.35	0.38	485	480
457	Jagiellonian Univ Krakow	2387.20	0.66	0.52	0.53	460	0.40	0.42	413	413
458	State Univ Campinas	4191.26	1.16	0.52	0.53	458	0.36	0.38	350	346
459	Lomonosov Moscow State Univ	2841.26	0.79	0.52	0.53	459	0.46	0.49	370	367
460	Waseda Univ	1883.84	0.52	0.51	0.51	465	0.41	0.43	443	441
461	Chungnam Natl Univ	1432.64	0.40	0.51	0.54	456	0.33	0.33	483	481
462	Univ Pretoria	1335.34	0.37	0.51	0.51	463	0.35	0.34	486	485
463	Univ Buenos Aires	3087.46	0.85	0.51	0.50	467	0.35	0.36	399	400
464	Fed Univ Rio Grande Sul	2555.78	0.71	0.51	0.51	464	0.37	0.38	418	417
465	Chulalongkorn Univ	1707.03	0.47	0.51	0.49	472	0.30	0.31	477	477
466	St Petersburg State Univ	889.78	0.25	0.50	0.52	462	0.36	0.38	492	492
467	Univ São Paulo	10690.19	2.96	0.50	0.51	466	0.36	0.36	164	167
468	Univ Chile	1935.23	0.54	0.48	0.49	470	0.29	0.30	470	471
469	Charles Univ Prague	3688.18	1.02	0.48	0.52	461	0.34	0.35	381	384
470	Banaras Hindu Univ	1271.27	0.35	0.48	0.50	468	0.41	0.43	476	475
471	Kanazawa Univ	2014.70	0.56	0.48	0.46	480	0.32	0.33	460	461
472	Chonnam Natl Univ	1841.86	0.51	0.48	0.47	475	0.33	0.34	466	465
473	Chang Gung Univ	1909.07	0.53	0.48	0.47	477	0.25	0.23	481	486
474	Natl Yang-Ming Univ	1895.99	0.52	0.47	0.43	489	0.26	0.25	478	482
475	Inha Univ	2063.41	0.57	0.47	0.49	471	0.26	0.28	473	473
476	Kyungpook Natl Univ	2122.77	0.59	0.47	0.47	478	0.37	0.38	438	440
477	Univ Fed Minas Gerais	2019.79	0.56	0.46	0.49	469	0.34	0.36	454	453
478	Kobe Univ	2539.51	0.70	0.46	0.47	476	0.37	0.38	416	416
479	Natl Autonomous Univ Mexico	5182.29	1.43	0.46	0.48	474	0.37	0.36	306	316
480	Huazhong Univ Sci & Technol	3840.69	1.06	0.45	0.45	481	0.32	0.34	386	383
481	King Saud Univ	878.85	0.24	0.44	0.49	473	0.32	0.36	495	493
482	Fed Univ Rio de Janeiro	3221.96	0.89	0.44	0.46	479	0.48	0.48	346	350
483	Okayama Univ	3007.19	0.83	0.44	0.43	486	0.35	0.35	401	409
484	Istanbul Univ	2739.43	0.76	0.44	0.45	482	0.30	0.30	434	437
485	Univ Malaya	1115.78	0.31	0.44	0.43	488	0.28	0.26	493	494
486	Univ Belgrade	2231.35	0.62	0.42	0.44	485	0.28	0.30	462	462
487	Fed Univ Viçosa	506.17	0.14	0.42	0.44	484	0.24	0.22	500	500
488	Fed Univ São Paulo	1806.32	0.50	0.41	0.38	495	0.26	0.25	480	484
489	Gazi Univ	1991.20	0.55	0.41	0.44	483	0.24	0.26	482	479
490	Tehran Univ Med Sci	1076.20	0.30	0.40	0.40	491	0.21	0.20	497	499
491	Univ Zagreb	2038.58	0.56	0.40	0.43	487	0.32	0.33	459	460

Rank T	University	Number articles	‰	Top 10% T	T*	Rank T*	Average high-impact gaps A	A*	Rank A	Rank A*
492	Univ Nacl La Plata	1402.41	0.39	0.39	0.40	492	0.24	0.24	491	491
493	Univ Estadual Paulista	2585.91	0.72	0.39	0.41	490	0.26	0.27	457	456
494	Nihon Univ	2114.86	0.59	0.39	0.39	493	0.25	0.27	472	474
495	Ankara Univ	2034.92	0.56	0.38	0.38	494	0.21	0.21	487	488
496	Pusan Natl Univ	2181.52	0.60	0.37	0.38	496	0.31	0.33	456	454
497	Hacettepe Univ	2745.60	0.76	0.36	0.36	497	0.29	0.29	440	444
498	Konkuk Univ	1238.67	0.34	0.36	0.35	498	0.21	0.21	496	496
499	Fed Univ Paraná	920.70	0.25	0.36	0.33	500	0.24	0.26	498	497
500	Catholic Univ Korea	1223.54	0.34	0.35	0.35	499	0.18	0.19	499	498
	Union of Leiden Ranking universities	1882370.33	520.79	1.14	1.13		1.18	1.16		
	Average over the 500 values	3764.74	1.04	1.01	1.01		1.01	0.98		
	SD	2775.21	0.77	0.36	0.35		1.37	0.52		
	CV	0.74	0.74	0.35	0.35		1.36	0.52		

Table B. Characteristics of overall citation distributions for the entire dataset of distinct articles (3.6 million), distinct articles with at least one LR university (2.4 million), and the fractional counting for LR universities (1.9 million)

Distributions	First mean μ_1	Second mean μ_2	Percentage of articles in category: 1	2	3	Percentage of citations in category: 1	2	3
3.6 million	8.7	24.0	72.0	20.2	7.8	22.6	32.2	45.2
2.4 million	9.8	26.5	71.5	20.8	7.7	23.0	32.9	44.1
1.9 million	9.8	25.0	70.9	20.7	8.4	26.3	31.6	42.1

Distributions	Robust coefficient of variation	GM index of skewness
3.6 million	0.75	0.64
2,4 million	0.75	0.71
1.9 million	0.94	0.75

$\boldsymbol{\mu_1}$ = mean citation

$\boldsymbol{\mu_2}$ = mean citation of articles with citations above μ_1

Category 1 = articles with a low citation, below μ_1

Category 2 = articles with a fair number of citations, above μ_1 and below μ_2

Category 3 = articles with a remarkable or outstanding number of citations, above μ_2

Table 1. Mean number of publications per cluster, m, and mean citation per publication, μ, in the partition by deciles of the overall citation distribution

		m	
Deciles			
	1	2,472.7	10.5
	2	1,435.3	9.4
	3	1,015.9	8.0
	4	737.3	7.4
	5	542.1	6.9
	6	377.4	5.8
	7	250.8	5.1
	8	151.3	4.5
	9	70.5	3.7
	10	6.0	1.2

A. Number of clusters	5,119
B. Number of small clusters[a]	858
C. Number of significant clusters[b]	4,161
D. % of articles in small clusters	0.89%

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[a] **Small clusters have less than or equal to 100 publications**

[b] **Significant clusters have more than 100 publications**

Table 2. The effect on overall citation inequality, $I(C')$, of the differences in citation impact between clusters before and after standard field-normalization, and the impact of normalization on this effect

		Normalization impact = 100 $[IDCC - IDCC^{*}/IDCC]$
Before normalization, 100 $[IDCC/I(C')]$	22.5 %	-
After normalization, 100 $[IDCC^{*}/I(C')]$	4.3 %	84.3 %
Results from Crespo *et al.* (2014) for 219 sub-fields		
Before normalization, 100 $[IDCC/I(C')]$	18.1 %	
After normalization, 100 $[IDCC^{*}/I(C')]$	3.3 %	87.3 %
Results from Li *et al.* (2013) for 172 sub-fields		
Before normalization, 100 $[IDCC/I(C')]$		
Average over six one-year datasets (Std. dev.)	13.1 % (0.9)	
After normalization, 100 $[IDCC^{*}/I(C')]$		
Average over six one-year datasets (Std. dev.)	2.9 % (0.4)	79.4 % (4.3)

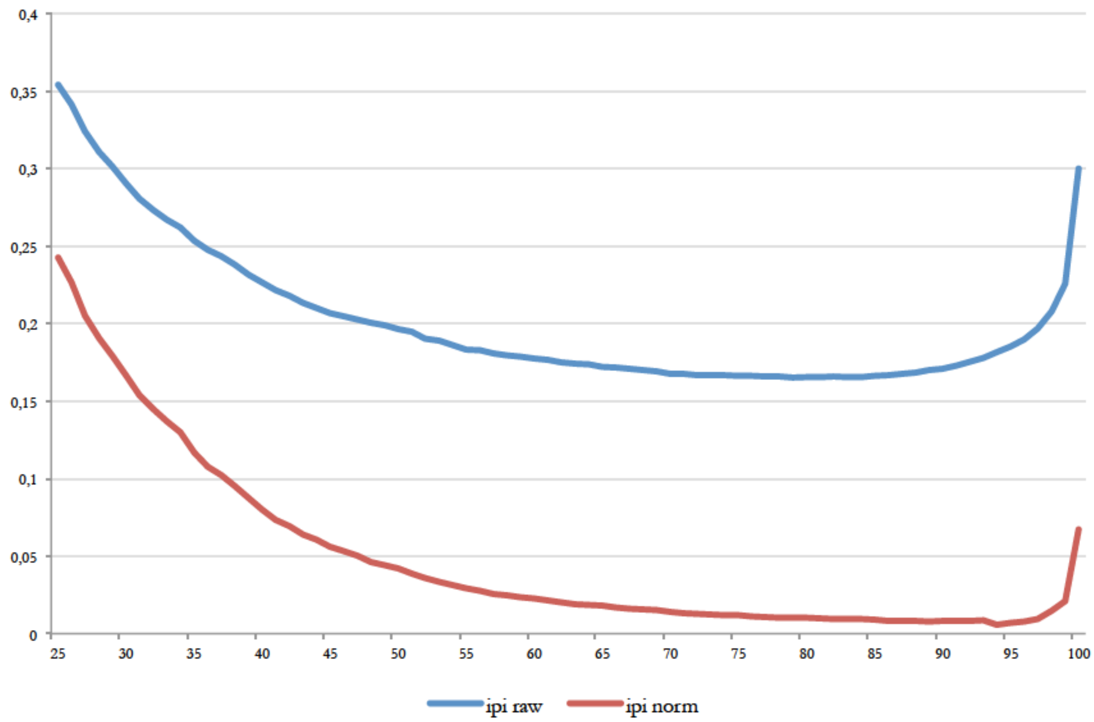

Figure 1. Overall citation inequality due to differences in citation practices, I(π), as a function of π. Results for the [25, 100] percentile interval

Table 3.A. Empty clusters in the sets of high-impact articles B and Y, and percentage of articles in the intersections $B \cap X$, and $Y \cap X$

Sets of high-impact articles	Number of empty clusters	% of articles in X in the empty clusters	% of articles in the intersection with X
B	1,078	2.67	65.8
Y	308	0.03	94.8

Table 3.b. Empty clusters in the sets of high-impact articles B' and Y', and percentage of articles in the intersections $B' \cap X'$, and $Y' \cap X'$

Sets of high-impact articles	Number of empty clusters	% of articles in X in the empty clusters	% of articles in the intersection with X
B'	117	1.37	66.6
Y'	308	0.00	94.9

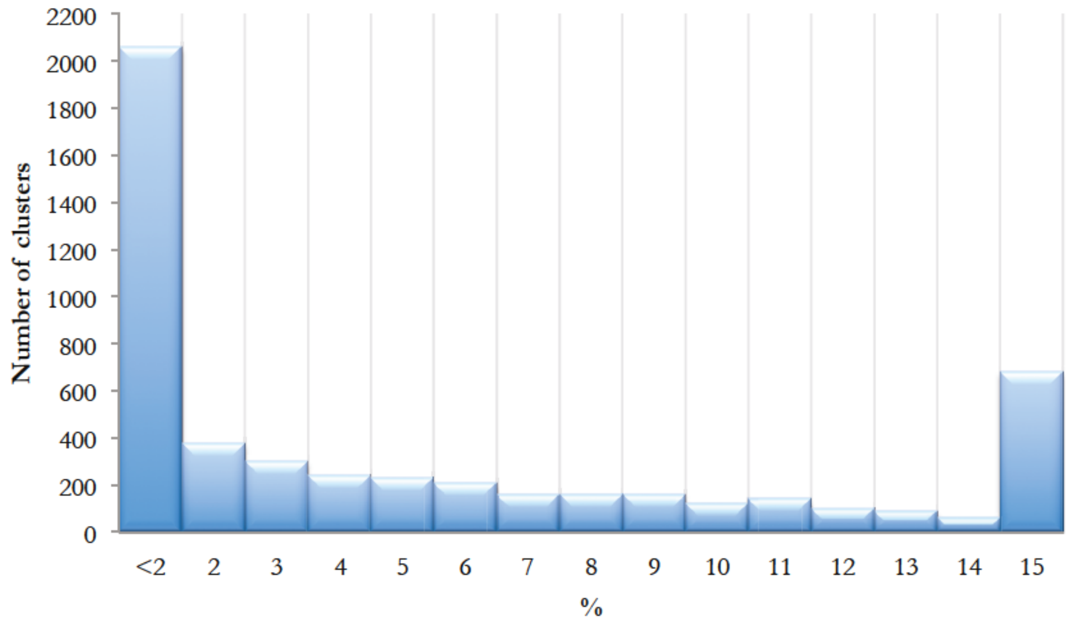

Figure 2.A. High-impact articles in the overall un-normalized citation distribution *C*. Histogram of the distribution over 5,119 clusters of the percentage that these articles represent in each cluster

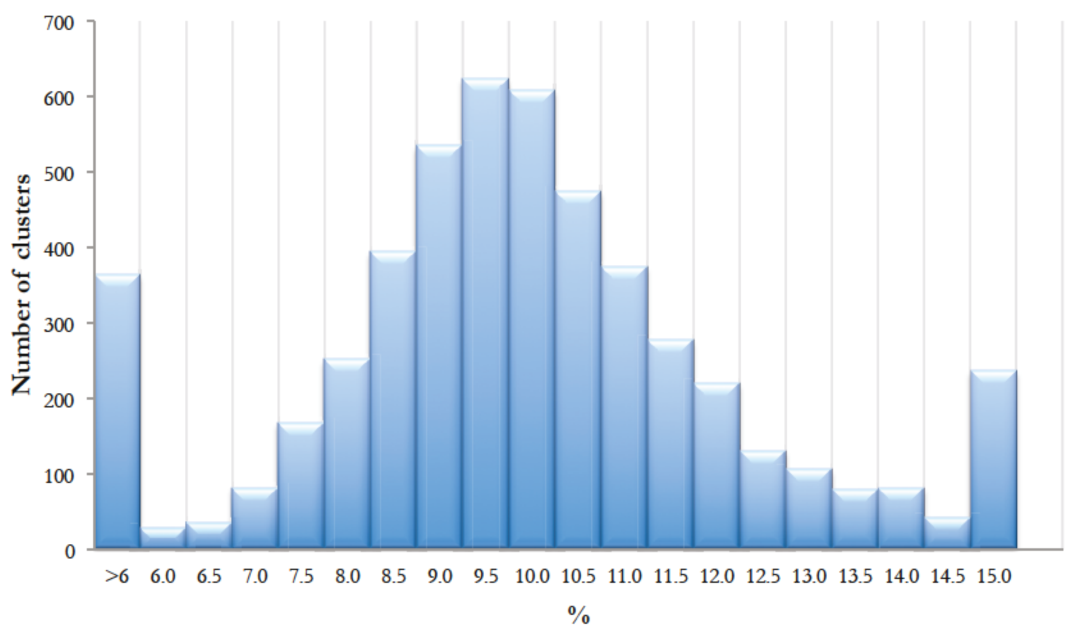

Figure 2.B. High-impact articles in the overall normalized citation distribution *C. Histogram of the distribution over 5,119 clusters of the percentage that these articles represent in each cluster**

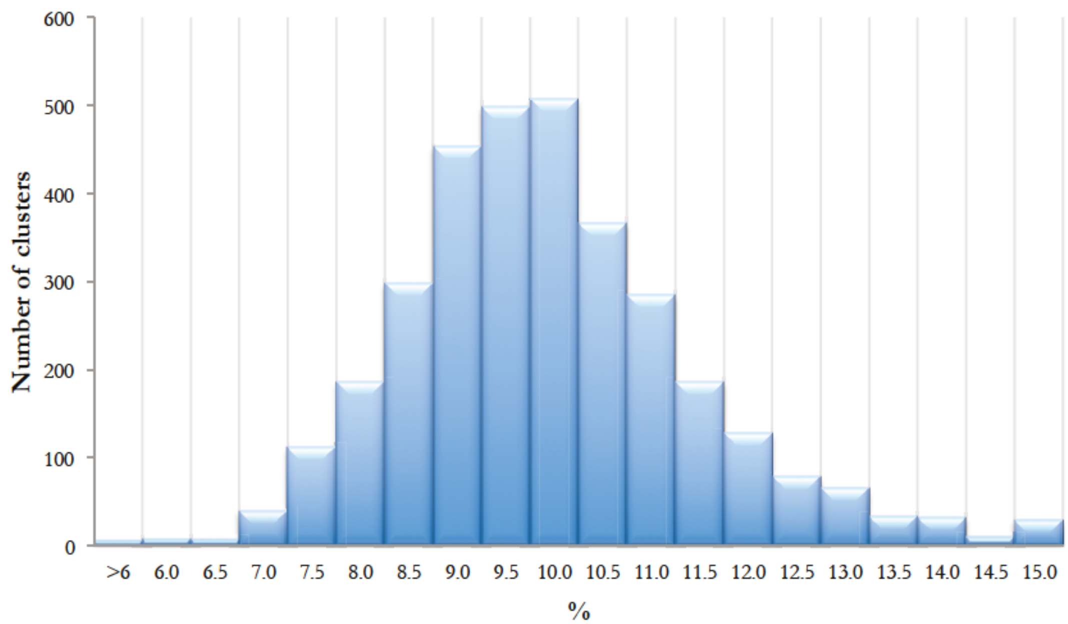

Figure 2.C. High-impact articles in the overall normalized citation distribution *C'. Histogram of the distribution over 3,332 clusters with more than 250 publications of the percentage that these articles represent in each cluster**

Table 4.A. University re-ranking according to the Top 10% indicator T

	From the WoS class. system to granularity level 8[a]			From T_i to T^*_i		
	First 100 universities	**Next 400 universities**	**Total**	**First 100 universities**	**Remaining 400 universities**	**Total**
> 50 positions	0	81	81	0	11	11
26 – 50	7	107	114	1	58	59
16 – 25	13	74	87	4	65	69
6 – 15	36	81	117	35	140	175
≤ 5 positions	44	57	101	52	108	160
No change[b]	-	-	-	8	18	26
Total	100	400	500	100	400	500

Table 4.B. University differences in T_i values

	From the WoS class. system to granularity level 8[c]			From T_i to T^*_i		
	First 100 uni	**Next 400 universities**	**Total**	**First 100 universities**	**Next 400 universities**	**Total**
> 0.20	1	16	17	0	0	0
> 0.10 and ≤ 0.2	12	66	78	3	8	11
> 0.05 and ≤ 0.1	27	124	151	26	49	75
≤ 0.05	60	94	254	71	343	414
Total	100	400	500	100	400	500

[a] Table 6.A in Ruiz-Castillo & Waltman (2015)
[b] Not available
[c] Table 6.B in Ruiz-Castillo & Waltman (2015)

Table 5.A. University re-rankings according to the Average of high-impact gaps indicator A

	First 100 universities	Remaining 400 universities	Total
> 50 positions	0	1	1
26 – 50	0	6	6
16 – 25	1	12	13
6 – 15	21	126	147
≤ 5 positions	70	220	290
No change	8	35	43
Total	100	400	500

Table 5.B. University differences in A_i values

	First 100 universities	Remaining 400 universities	Total
> 0.20	5	3	8
> 0.10 and ≤ 0.2	57	38	95
> 0.05 and ≤ 0.1	31	157	188
≤ 0.05	7	202	209
Total	100	400	500