University Citation Distributions

Antonio Perianes-Rodriguez[1] and Javier Ruiz-Castillo[2]

[1] *antonio.perianes@uc3m.es*
Universidad Carlos III, Department of Library and Information Science, SCImago Research Group, C/ Madrid, 128, 28903 Getafe, Madrid (Spain)

[2] *jrc@eco.uc3m.es*
Universidad Carlos III, Departamento de Economía, C/ Madrid, 126, 28903 Getafe, Madrid (Spain)

Abstract
In this paper we investigate the characteristics of the citation distributions of the 500 universities in the 2013 edition of the CWTS Leiden Ranking. We use a WoS dataset consisting of 3.6 million articles published in 2003-2008 with a five-year citation window, and classified into 5,119 clusters. The main findings are the following four. Firstly, The universality claim, according to which all university citation distributions, appropriately normalized, follow a single functional form, is not supported by the data. Secondly, nevertheless, the 500 university citation distributions are all highly skewed and very similar. Broadly speaking, university citation distributions appear to behave as if they differ by a relatively constant scale factor over a large, intermediate part of their support. Thirdly, citation impact differences between universities account for 3.85% of overall citation inequality. However, these differences are greatly reduced when university citation distributions are normalized using their MNCS values as normalization factors. Finally, the above results have important practical consequences. On one hand, we only need a single explanatory model for the single type of high skewness characterizing all university citation distributions. On the other hand, the similarity of university citation distributions goes a long way in explaining the similarity of the university rankings obtained with the MNCS and the top 10% indicator.

Conference Topic
Citation and co-citation analysis

Introduction
Universities constitute a key vehicle in the production of knowledge in contemporary societies. However, the evaluation of the quality, or the relevance of the research done by universities in a myriad of scientific fields is a very difficult problem. For the assessment of the performance of research units of all types during the last decades, academic bodies, public officials in charge of science policy, and specialists in the field of Scientometrics have been paying increasing attention to one observable aspect of research in all fields: the citation impact of publications in the periodical literature.

In this paper, we focus on this aspect of research for the 500 universities included in the 2013 edition of the CWTS Leiden Ranking (LR universities) (Waltman et al., 2012a). We use a Web of Science (WoS) dataset consisting of 3.6 million publications in the 2005-2008 period, the citations they receive during a five-year citation window for each year in that period, and a classification system consisting of 5,119 clusters (Ruiz-Castillo & Waltman, 2015).

The construction of university citation distributions in the all-sciences case requires the prior solution of two methodological problems: the assignment of responsibility for publications with two or more co-authors belonging to different institutions, and the aggregation of the citation impact achieved by research units working in different scientific clusters. We solve these problems using a fractional counting approach in the presence of co-authorship, and the standard field-normalization procedure where cluster mean citations are used as normalization factors.

Once these two problems have been solved, specialists typically debate the properties of alternative citation impact indicators. In this paper, we study a basic aspect of the research evaluation problem that comes *before* the comparison of the advantages and shortcomings of specific indicators, namely, the characteristics of the university citation distributions themselves. These distributions arise from the interplay of a complex set of economic, sociological, and intellectual factors that influence in a way hard to summarize the research performance of each university in every field. In this scenario, it is well known that some universities are more productive or successful than others in terms of the number of publications and/or the mean citation that these publications receive. However, little is known concerning the shape of university citation distributions abstracting from size and mean citation differences. In order to contribute to this knowledge, in this paper we investigate the following four issues.

Firstly, we inquire whether university citation distributions are universally distributed. The universality condition, borrowed from statistical physics, means that, appropriately normalized, citation distributions follow a unique functional form within the bounds set by random variation. Radichhi *et al.* (2008) suggest a statistical test of this condition in their study of 14 WoS journal subject categories. According to this test, the universality condition is not satisfied for our 500 university citation distributions. This is consistent with previous results for large classification systems in WoS datasets consisting of complete field citation distributions that include publications with zero citations (Albarrán & Ruiz-Castillo, 2011, Albarrán *et al.*, 2011a, Waltman *et al.*, 2012a, Perianes-Rodriguez & Ruiz-Castillo, 2014).

Secondly, in view of the above finding, we ask: are at least university citation distributions as highly skewed and as similar among each other as previous results indicate for field citation distributions? Using the same size- and scale-independent techniques that have been used in previous research, we confirm that this is the case in our dataset. This result has been established at different aggregation levels, publication years, and citation window lengths, and independently of whether the problem of the multiple assignment of publications to sub-fields in WoS datasets is solved by following a multiplicative or a fractional approach (Glänzel, 2007, Radicchi *et al.*, 2008, Albarrán & Ruiz-Castillo, 2011, Albarrán *et al.*, 2012, Herranz & Ruiz-Castillo, 2012, Waltman *et al.*, 2012a, Radicci & Castellano, 2012, Li *et al.*, 2013, Ruiz-Castillo & Waltman, 2015, Perianes-Rodriguez & Ruiz-Castillo, 2014). Similar conclusions concerning the skewness and similarity of individual productivity distributions are found when authors are classified into 30 broad scientific fields (Ruiz-Castillo & Costas, 2014).

Thirdly, using the measuring framework introduced in Crespo *et al.* (2013), we investigate how important is the effect of differences in citation impact between LR universities in the overall citation inequality in the union of the 500 LR university citation distributions. Furthermore, we inquire up to what point this effect can be accounted for by scale factors captured by the universities' Mean Normalized Citation Score (*MNCS* hereafter). The answer is that citation impact differences between universities account for 3.85% of overall citation inequality –a much smaller percentage than what is found in the context of production and citation practice differences between scientific fields (Crespo *et al.*, 2013, 2014, Ruiz-Castillo & Waltman, 2015, Perianes-Rodriguez & Ruiz-Castillo, 2014). These differences are greatly reduced when university citation distributions are normalized using their *MNCS* values as normalization factors.

Finally, we discuss the implications of these results for the understanding of the high correlation between the university rankings according to two citation impact indicators: the *MNCS*, and the Top 10% indicator of scientific excellence (the $PP_{top\ 10\%}$ indicator hereafter), defined as the percentage of an institution's output included into the set formed by 10% of the world most cited papers in the different scientific fields. The latter indicator has been recently adopted by well-established institutions, such as the CWTS in the Netherlands, and SCImago in Spain.

The rest of the paper is organized into two Sections. The first section presents the empirical results, while the next section discusses further research.

Empirical results

The universality of university citation distributions

Let $\boldsymbol{c_i}$ be the LR university i field-normalized citation distribution. Note that, for each university, the mean citation of $\boldsymbol{c_i}$ is precisely the Mean Normalized Citation Score (MNCS hereafter). Let $\boldsymbol{c^*_i}$ be the normalized citation distribution of university i using the university MNCS as the normalization factor. Let $\boldsymbol{C^*}$ be the union of the universities' normalized citation distributions, $\boldsymbol{C^*} = \cup_i \{\boldsymbol{c^*_i}\}$, where publications are ranked in increasing order of the number of normalized citations. Let $\boldsymbol{X_z}$ be the set of publications in the top z% of distribution $\boldsymbol{C^*}$, and let $\boldsymbol{x_{zi}}$ be the publications in X_z that belongs to the i-th university, so that $\boldsymbol{X_z} = \cup_i \{\boldsymbol{x_{zi}}\}$. In the terminology of Radicchi *et al.* (2008), if the ranking is fair, or unbiased, the percentage of publications that the set $\boldsymbol{x_{zi}}$ represents within each university should be near z% with small fluctuations. Let N_c and N_i be, respectively, the number of universities and the number of publications in the i-th university. Assuming that publications of the various universities are scattered uniformly along the rank axis, for any value z% one would expect the average relative frequency of the number of articles in any university to be z% with a standard deviation $\sigma_z = \{[z(100 - z)\Sigma_{\mathrm{i}} (1/N_i)]/N_c\}^{1/2}$, which is equation (2) in Radicchi *et al.* (2008).

Table 1. Percentage of publications in each sub-field that appear in the top z% of the global rank, together with the standard deviation, σ_z, and the coefficient of variation, σ_z/z.

Theoretical values			Normalised distribution		
z%	σ_z	σ_z/z	z%	σ_z	σ_z/z
(1)	(2)	(3)	(4)	(5)	(6)
1	0.20	0.20	0.96	0.29	0.30
5	0.43	0.09	4.95	0.90	0.18
10	0.59	0.06	10.00	1.46	0.15
20	0.79	0.04	20.03	2.41	0.12
30	0.91	0.03	30.04	3.11	0.10
40	0.97	0.02	40.00	3.49	0.09
50	0.99	0.02	49.88	3.76	0.08
75	0.86	0.01	74.73	4.08	0.05
90	0.59	0.01	88.94	4.08	0.05

For each z value in a certain sequence, column 2 in Table 1 presents the standard deviations σ_z, while column 3 is the theoretical coefficient of variation, namely, σ_z/z. Columns 4 to 6 contain the values for the average z, the standard deviation σ_z, and the coefficient of variation σ_z/z obtained empirically in distribution $\boldsymbol{C^*}$.

Although σ_z varies non-linearly with z, the theoretical coefficient of variation in column 3 raises from 0.01 to 0.20 when we proceed from z = 90% towards z = 1%. In the normalized case, the considerable differences with the theoretical values in column 6, above all for lower values of z, indicate the lack of universality for this set of 500 university citation distributions. This conclusion contrasts with the universality claim in Chatterjee *et al.* (2014), who study 42 academic institutions across the world, their publications in four years, 1980, 1990, 2000, and 2010, and the citations they receive according to the WoS until July 2014. We should emphasize that this paper has a number of technical problems. The criterion for selecting their

42 academic institutions is not given, and there is no information on how the following three problems have been solved: the assignment of publications in WoS datasets to multiple journal subject categories, the assignment of responsibility for co-authored publications, and the all-sciences aggregation problem. Nevertheless, we will proceed discussing their results. Chatterjee *et al.* (2014) explain that, for each publication year, the university normalized citation distributions fit well to a lognormal for most of the range, although the poorly cited publications seem to follow another distribution, while the upper tail is better described by a power law. This is quite different from the claim that there is a single functional form for the entire domain of definition of the 42 institutions in their sample. Our statistical approach tests whether the universality claim is supported by the data over the entire domain of the 500 LR universities. In this sense, our results do not contradict each other. We both agree that the universality claim over the entire domain is not the case in our respective samples.

On the other hand, the main problem with the still unpublished version of Chatterjee *et al.* (2014) is that, in our opinion, their statistical methods are not clearly explained. Unfortunately, the authors do not explain the following three aspects: (i) how the partition of the domain into three segments is estimated for each university, and whether this partition is universal; (ii) which tests have been used to determine the functional form chosen in each segment versus possible alternatives; (iii) how the confidence interval for the power law parameter has been estimated, and which is the confidence interval for the lognormal parameters. As a matter of fact, the only clear evidence for the distributions collapse into a universal curve is the graphical illustration provided for a sample –whose selection is unexplained– of 24 of the original 42 academic institutions.

The skewness and similarity of university citation distributions

The skewness of citation distributions is assessed by simply partitioning citation distributions into three classes of articles with low, fair, and very high number of citations. For this purpose, we follow the Characteristic Scores and Scale (CSS hereafter) approach, first introduced in Scientometrics by Schubert *et al.* (1987). In our application of the CSS technique, the following two *characteristic scores* are determined for every university: μ_1 = mean citation, which in our context is equal to the *MNCS*, and μ_2 = mean citation for articles with citations greater than μ_1. We consider the partition of the distribution into three broad categories: (i) articles with a low number of citations, smaller than or equal to μ_1; (iii) fairly cited articles, with a number of citations greater than μ_1 and smaller than or equal to μ_2, and (iii) articles with a remarkable or outstanding number of citations greater than μ_2. For each citation distribution, we measure the percentages of publications in the three categories, as well as the percentages of the total citations accounted for by the three categories. The average, standard deviation, and coefficient of variation for the 500 university values of the percentages of publications, the percentages of the total citations in the three categories are included in Table 2.

The results are remarkable. In principle, differences in resources, intellectual traditions, organization, the structure of incentives, and other factors lead us to expect large differences between the 500 LR university citation distributions in different parts of the world. However, judging from the size of the standard deviations and the coefficient of variations for the 500 universities, we find that university citation distributions are extremely similar. At the same time, the distributions are highly skewed: on average, the MNCS values of the 500 universities is 12.9 percentage points above the median, while the 12.5 of outstanding articles account for 44.4% of all normalized citations.

Table 2. The skewness of citation distributions according to the CSS approach. Percentages of articles, and percentages of citations by category. Average, standard deviation, and coefficient of variation over the 500 LR universities, and results for the overall citation distribution.

	Percentage of articles in category:			Percentage of citations in category:		
	1	**2**	**3**	**1**	**2**	**3**
Average (Std. deviation)	62.9 (1.9)	24.6 (1.2)	12.5 (1.2)	22.9 (1.7)	32.7 (0.8)	44.4 (1.5)
Coefficient of variation	0.03	0.05	0.10	0.08	0.02	0.03

For the sake of robustness, we have conducted two more sets of computations. In the first place, in the presence of co-authorship we have assigned publications to universities in a multiplicative way. In the second place, we have studied the raw citation distributions without the benefit of any field-normalization procedure. Interestingly enough, the results are very similar to those obtained for field-normalized university citation distributions in the fractional case. Thus, we conclude that the characteristics of university citation distributions are robust to the way the assignment of publications to universities in the presence of co-authorship and the all-sciences aggregation problem are solved.

Finally, we should mention the results of two contributions closer to our own in which research publications are aggregated into the type of organization unit to which the authors belong. Firstly, Albarrán *et al.* (2015) study the partition of world citation distributions into 36 countries and two residual geographical areas using a dataset, comparable to ours, consisting of 4.4 million articles published in 1998-2003 with a five-year citation window for each year. They find that, at least in some broad fields and in the all-sciences case, the country citation distributions are not only highly skewed, but also very similar across countries –a result parallel to our own for the 500 LR universities. Secondly, Perianes-Rodriguez & Ruiz-Castillo (2015) study a set of 2,530 highly productive economists who work in 2007 in a selection of the top 81 economics departments in the world. Contrary to previous results for field or country citation distributions, we find that productivity distributions are very different across the 81 economics departments. However, the data in Perianes-Rodriguez & Ruiz-Castillo (2015) does not consist of department citation distributions of articles published in a certain period of time with a citation window of common length, but of the individual productivity of faculty members in each department, where individual productivity is measured as a quality index that weights differently the articles published up to 2007 by each researcher in four journal equivalent classes. Nevertheless, we cannot rule out that the similarity of citation distributions is a phenomenon present at certain aggregate levels. To settle this issue, we need more work at the department level with citation distributions articles published in a certain period of time with a common citation window.

The importance of citation impact differences between universities

Together with the assessment of the between-group variability concerning the shape of university citation distributions, we are interested in measuring how important are the citation impact differences between universities. Formally, this problem is analogous to the measurement of the importance of differences in production and citation practices between scientific fields. For the latter, Crespo *et al.* (2013) suggested to measure the impact of such differences on the overall citation inequality for the entire set of field citation distributions applying an additively decomposable citation inequality index to a double partition into scientific fields and quantiles. Similarly, in our case we measure how much of the overall citation inequality exhibited by the union of the 500 LR university citation distributions can be attributed to the citation impact differences between universities (this is also the approach adopted in Perianes-Rodriguez & Ruiz-Castillo, 2014a, to assess the effect of citation impact between countries).

For that purpose, we begin with the partition of, say, each university citation distribution into Π quantiles, indexed by $\pi = 1,.., \Pi$. In practice, in this paper we use the partition into percentiles, that is, we choose $\Pi = 100$. Assume for a moment that, in any university u, we disregard the citation inequality within every percentile by assigning to every article in that percentile the mean citation of the percentile itself, μ_u^{π}. The interpretation of the fact that, for example, $\mu_u^{\pi} = 2\,\mu_v^{\pi}$ is that, on average, the citation impact of university u is twice as large as the citation impact of university v in spite of the fact that both quantities represent a common underlying phenomenon, namely, the same *degree of citation impact* in both universities. In other words, for any π, the distance between μ_u^{π} and μ_v^{π} is entirely attributable to the difference in the citation impact that prevails in the two universities for publications with the same degree of excellence in each of them. Thus, the citation inequality between universities at each percentile, denoted by $I(\pi)$, is entirely attributable to the citation impact differences between the 500 LR universities holding constant the degree of excellence in all universities at quantile π. Hence, any weighted average of these quantities, denoted by *IDCU* (*I*nequality due to *D*ifferences in *C*itation impact between *U*niversities), provides a good measure of the total impact on overall citation inequality that can be attributed to such differences. Let $\boldsymbol{c_i}$ be university i citation distribution, and let $\boldsymbol{C}$ be the union of the universities citation distributions, $\boldsymbol{C} = \cup \{\boldsymbol{c_i}\}$. We use the ratio

$$IDCU/I(\boldsymbol{C}) \tag{1}$$

to assess the relative effect on overall citation inequality, $I(\boldsymbol{C})$, attributed to citation impact differences between universities (for details, see Crespo *et al.*, 2013).

Finally, we are interested in estimating how important scale differences between university citation distributions are in accounting for the effect measured by expression (1). Following the experience in other contexts, we choose the university mean citations as normalization factors. To assess the importance of such scale factors, we use the relative change in the *IDPD* term, that is, the ratio

$$[IDCU - IDCU^{*}]/IDCU, \tag{2}$$

where *IDCU** is the term that measures the effect on overall citation inequality attributed to the differences in university distributions after the normalization of university citation distributions using university mean citations as normalization factors (for details, see again Crespo *et al.*, 2013). The estimates for expressions (1) and (2) in our dataset are included in table 3:

Table 3. The effect on overall citation inequality, I(C), of the differences in citation impact between universities before and after MNCS normalization, and the impact of normalization on this effect.

		Normalization impact = 100 [*IDPD – IDCP*/IDCP*]
Before MNCS normalization, 100 [*IDPU*/*I*(*C*)]	3.85 %	-
After MNCS normalization, 100 [*IDPU/*I*(*C*)]**	0.72 %	81.9 %

It is interesting to compare these figures with what was obtained in two instances in the previous literature. The first case concerns the partition into 36 countries and two residual geographical areas in the all-sciences case (Albarrán *et al.*, 2014), while the second case refers to 219 WoS sub-fields (Crespo *et al.*, 2014). Two comments are in order. Firstly, the effect on overall citation inequality due to citation impact differences between the 500 LR universities (3.85%) is comparable to the effect due to citation impact differences between countries (5.4%). However, both of them are considerably smaller than the corresponding effect on overall citation inequality attributable to differences in production and citation practices across the 219 sub-fields (approximately 18%). Secondly, the reduction of the total effect generated by *MNCS* normalization in our dataset (81.9% of the total effect) is of a comparable order of magnitude to the same phenomenon in the context of country (85.2%) or sub-field citation distributions (83.2%).

It should be noted that these results summarize in a pair of scalars a complex phenomenon that takes place along the entire support of our university citation distributions. As a matter of fact, the term *IDCU* is simply a weighted average of the $I(\pi)$ terms, $\pi = 1,\ldots, 100$, that capture the effect on overall inequality of the citation impact differences between the 500 LR universities holding constant the degree of excellence in all universities at percentile π. Therefore, it is instructive to study how $I(\pi)$ changes with π both before and after the MNCS normalization. The results appear in Figure 1 (since $I(\pi)$ is very high for $\pi < 27$, for clarity these percentiles are omitted from Figure 1), which deserves the following two comments. Firstly, the strong impact of *MNCS* normalization is readily apparent. Secondly, it is useful to informally partition the support of our citation distributions into the following three intervals: [0, 57], [58, 96], and [98, 100]. In the first and the third one, $I(\pi)$ values are very high. This means that, since in these two intervals university 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. Thus, this is the range of values where the search for a single functional form in Chatterjee *et al.* (2014) may give good results in our dataset.

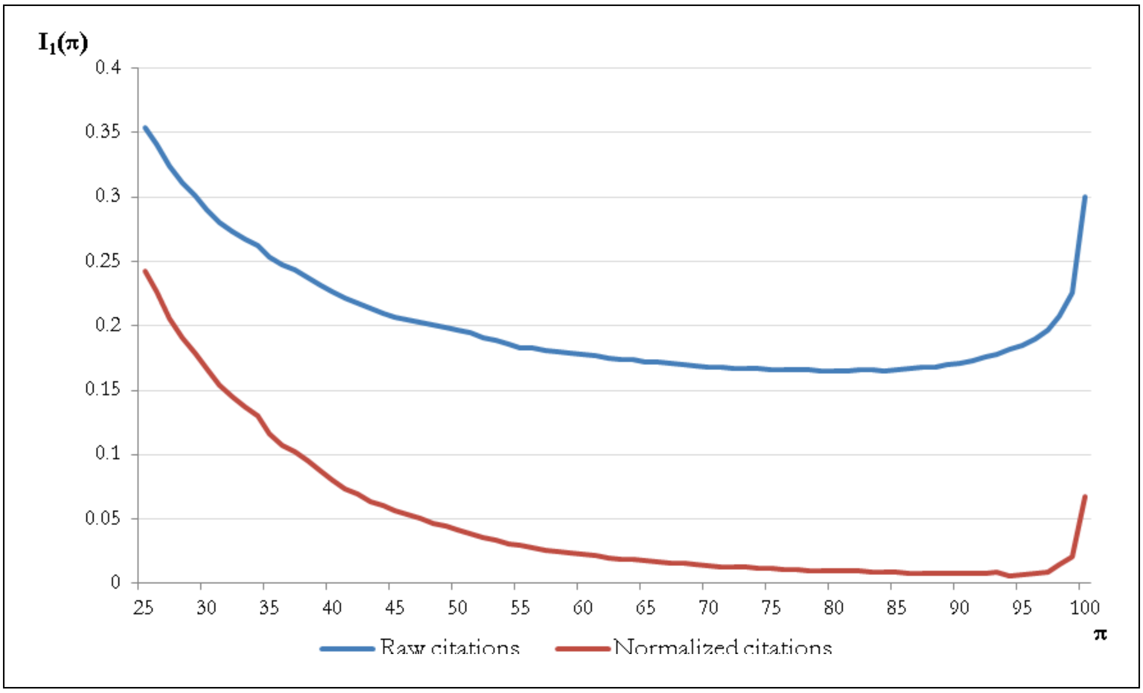

Figure 1. Citation Inequality Due to Differences in Citation Practices, $I(\pi)$, as a function of π. Results for the [27, 100] quantile interval.

Implications of the results

Our results have two types of practical implications. In the first place, assume that the top, intermediate, and worse universities have different types of citation distributions. In this case, we would need to build different models to explain the citation impact variability within the universities of the three types. On the contrary, since we have found that, although not universal, university citation distributions are rather similar, we need a single model to explain the high within-universities variability.

In the second place, recall that the move in the CWTS and SCImago rankings from an average-based citation impact indicator –such as the *MNCS*– towards a rank percentile approach that throws all the weight on the top *x*% of most cited papers –such as the $PP_{top\ 10\%}$ indicator– is surely due to the idea that, for highly skewed citation distributions, average-based indicators might not represent well the excellence in citation impact. However, the two rankings are rather similar: the Pearson correlation coefficient between university values is 0.981, while the Spearman correlation coefficient between ranks is 0.986. The situation is illustrated in Figure 2, where the positive slope indicates that to low (high) *MNCS* values there correspond lower (higher) $PP_{top\ 10\%}$ values.

We conclude that ordinal differences between the university rankings according to the MNCS and the $PP_{top\ 10\%}$ indicators are of a small order of magnitude. As a matter of fact, we find a strong, more or less linear relationship between the $PP_{top\ 10\%}$ and the MNCS in two other instances: for the 500 universities in the 2011/2012 edition of the Leiden Ranking (see Figure 2 in Waltman *et al.*, 2012b), and for the partition of the world into 39 countries and eight geographical areas studied in Albarrán and Ruiz-Castillo (2012). How can we explain these results? We have seen already that, university citation distributions behave as if they differ by a relatively constant scale factor over the [58, 96] percentile interval in their support. In this empirical scenario, it is not surprising that the MNCS values, which are reached at approximately the 63th percentile of citation distributions, and the $PP_{top\ 10\%}$ indicator that focus on the last 10 percentiles, provide very similar rankings. A convenient practical consequence is that the citation impact university ranking provided by the MNCS indicator is an adequate one. The $PP_{top\ 10\%}$ indicator would only add greater cardinal differences between the best and worse universities with relatively few re-rankings.

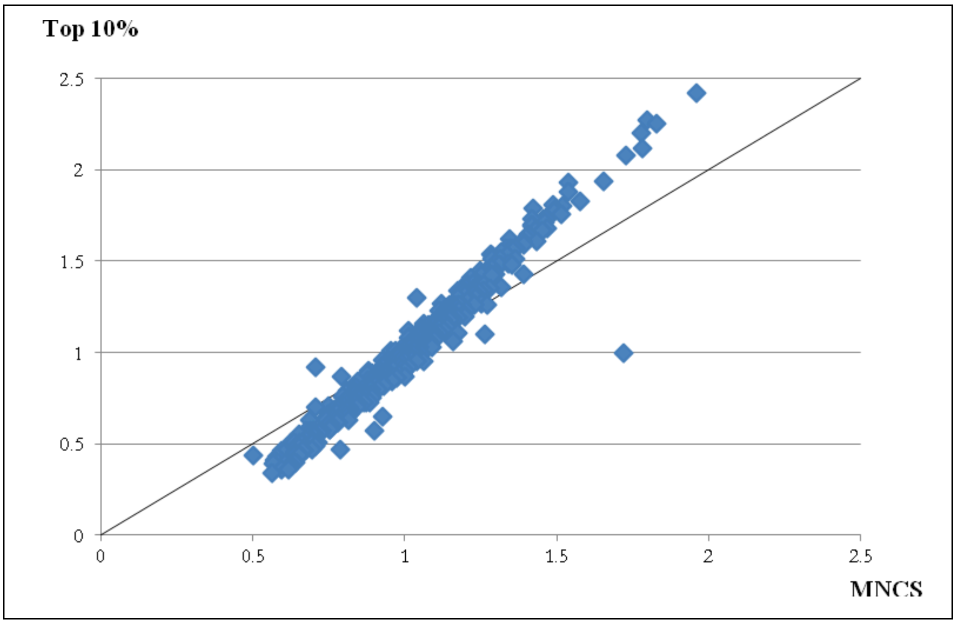

Figure 2. Scatterplot of the relation between the MNCS indicator and the PPtop 10% indicator for the 500 Leiden Ranking universities

It should be noted that further details concerning the following topics can be found in the Working Paper version of this paper, Perianes-Rodriguez & Ruiz-Castillo, 2014b): (i) the distribution of the total number of publications by universities; (2) the means μ_1 and μ_2, as well as the results of the CSSS approach for individual universities; (3) the graphical illustration of these results; (4) the measurement of the skewness of university citation distributions by means of a skewness index robust to extreme observations; (5) the robustness of all skewness results for the assignment of publications to universities in a multiplicative way, as well as the treatment of raw citation distributions without the benefit of any field-normalization procedure; (6) the re-rankings involved in the move from the MNCS towards the $PP_{top\ 10\%}$ indicator, as well as the cardinal differences between their values. In any case, the robustness of all of our results must be investigated with other datasets characterized by other publication years, and other citation windows, as well as other data sources different from the WoS.

Further research

Here are the possibilities for further research:

1. The effect on overall citation inequality attributable to the differences in citation impact between universities shows a characteristic pattern: broadly speaking, university citation distributions appear to behave as if they differ by a relatively constant scale factor over a large, intermediate part of their support. Consequently, it might be interesting to compute the exchange rates introduced in Crespo *et al.* (2013, 2014) to exploit this feature, and to use them as normalization factors. More generally, one could experiment with other normalization approaches that have been found useful in other contexts, notably the two parameter scheme introduced by Radicci & Castellano (2012).
2. Chatterjee *et al.*'s (2014) idea of fitting specific functional forms to university citation distributions in different intervals of their support is worth pursuing. The threshold determining the upper tail where a power law might be the best alternative could be estimated following the methods advocated in Clauset *et al.* (2009). Similar grid techniques could be applied to determine the lower bound of the interval where a lognormal might be the best alternative. In any case, standard methods should be used to test which specific functional form is best in each interval, as well as to estimate the parameters' confidence intervals (Thelwall & Wilson, 2014, and Brzezinski, 2015).
3. As we have seen in Section III.4, differences in citation impact between universities after MNCS normalization tend to rise when we reach the last few percentiles including the most highly cited articles. The question left for further research is how to complement average-based or $PP_{top\ 10\%}$ indicators with other measurement instruments that highlight the behavior of citation distributions over the last few percentiles. Given the important role of extreme observations in citation distributions, robustness of alternative high-impact indicators to these extreme situations will be an important element in the discussion.
4. Consider an array of citation distributions with a smaller number of scientific fields than in this paper in the columns, and the 500 LR universities in the rows. We already know much concerning field citation distributions and university citation distributions in the all-sciences case. A possible next step is to study the characteristics of university citation distributions column by column, that is, restricted to each field. The results will determine to what extent the similarities between citation distributions is a question depending on the aggregation level at which the study is conducted.

References

Albarrán, P., & Ruiz-Castillo, J. (2011). References made and citations received by scientific articles. *Journal of the American Society for Information Science and Technology*, *62*, 40–49.

Albarrán, P. and Ruiz-Castillo, J. (2012). *The Measurement of Scientific Excellence Around the World*. Working Paper, Economic Series 12-08, Universidad Carlos III (http://hdl.handle.net/10016/13896).

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.

Albarrán, P., Perianes-Rodriguez, A., & Ruiz-Castillo, J. (2014). Differences in citation impact across countries. *Journal of the American Society for Information Science and Technology*. *66*, 512-525.

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

Chatterjee, A., Ghosh, A., and Chakrabarty, B. K. (2014). *Universality of citation distributions for academic institutions and journals*, 29 September, arViv:1409.8029 [physics.soc-ph].

Clauset, A., C. R. Shalizi, and M. E. J. Newman (2009). Power-law Distributions In Empirical Data. *SIAM Review*, *51*, 661-703.

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 Association for Information Science and Technology*, *65*, 1244–1256.

Glänzel, W. (2007). Characteristic scores and scales: A bibliometric analysis of subject characteristics based on long-term citation observation. *Journal of Informetrics*, *1*, 92–102.

Herranz, N., & Ruiz-Castillo, J. (2012). Multiplicative and fractional strategies when journals are assigned to several sub-fields. *Journal of the American Society for Information Science and Technology*, *63*, 2195–2205.

Leydesdorff, L., Radicchi, F., Bornmann, L., Castellano, C., and de Nooye, W. (2012). Field-normalized Impact Factors: A Comparison of Rescaling versus Fractionally Counted Ifs. *Journal of the American Society for Information Science and Technology*, *27*, 292-306.

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. & Ruiz-Castillo, J. (2015). Within- and between-department variability in individual productivity. The case of economics. *Scientometrics*, *102*: 1497-1520.

Perianes-Rodriguez, A. & Ruiz-Castillo, J. (2014). *University citation distributions*. Working Paper, Economic Series 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. & Costas, R. (2014). The Skewness of Scientific Productivity. *Journal of Informetrics*, *8*, 917-934.

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). A New Methodology for Ranking Scientific Institutions". *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., Van Eck, N. J., & Van Raan, A. F. J. (2012a). Universality of citation distributions revisited. *Journal of the American Society for Information Science and Technology*, *63*, 72–77.

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. (2012b). The Leiden Ranking 2011/2012: Data collection, indicators, and interpretation. *Journal of the American Society for Information Science and Technology*, *63*, 2419–2432.