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## Abstract

In this article, we revisit the analysis of Laband and Tollison (2006) who documented that articles with two authors in alphabetical order are cited much more often than non-alphabetized papers with two authors in the American Economic Review and the American Journal of Agricultural Economics. Using more than 120,000 multi-authored articles from the Web of Science economics subject category, we demonstrate first that the alphabetization rate in economics has declined over the last decade. Second, we find no statistically significant relationship between alphabetized co-authorship and citations in economics using six different regression settings (the coefficients are very small). This result holds when accounting for intentionally or incidentally alphabetical ordering of authors. Third, we show that the likelihood of non-alphabetized co-authorship increases the more authors an article has.

JEL-Codes: A120, A140.

Keywords: alphabetization, co-authorship, citations, Web of Science.

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# 1 Introduction

Citations are frequently used to evaluate the usefulness of research. The novelty and popularity of research, for example, is reflected in how certain ideas are taken up by colleagues and become part of the established knowledge in a field. On the other hand, citations are key factors for measuring personal and institutional success in academia. In particular, citation counts, journal impact factors (JIFs, Clarivate Analytics) and journal rankings (Bornmann, Butz, and Wohlrabe 2018) are key elements for authors' and institutions' rankings. They have an immediate impact on the career of economists as a means of competition on the academic job market. Further, they serve as an important way of indicating the quality of research when it comes to decisions concerning tenures or the appropriation of research grants. However, factors other than quality potentially affect the number of citations a particular document receives (Tahamtan and Bornmann 2018).

Laband and Tollison (2006) (henceforth LT) investigated one of these potential effects, that of alphabetized co-authorship on citations. LT use a simple ordinary least squares (OLS) regression approach by controlling several aspects that might affect the citation rate of an article, i.e. number of pages, authors, tables and self-citations. LT showed that articles with two authors in alphabetical order accrue significantly more citations than those which are not. However, this finding does not hold true for three or more authors of an article. They conclude that the optimal team size for articles is two. LT based their investigation on a small sample consisting of the *American Economic Review* and the *American Journal of Agricultural Economics*, using data from the 1980s and 1990s, respectively. But does their conclusion hold true for other journals, e.g. less prestigious journals, and more recent articles? Is there a general relationship between author ordering and citations in economics?

In this article, we revisit and extend LT's analysis using a much larger data set of more than 120,000 multi-authored articles from 1990 to 2013 published in 307 economics journals. The article is structured in three parts. First, we offer an overview of alphabetization patterns

across both time and journals. Second, we investigate whether there is a relationship between alphabetized co-authorship and citations. We employ six different regression settings to ensure the robustness of the results. We check the robustness of our results also with respect to intentionally or incidentally alphabetical ordering. Third, we investigate the relationship between alphabetized co-authorship and citations for each journal in our sample and over time.

## 2 Data and descriptive statistics

In reflection of the core results by LT, we first broaden our descriptive analysis of alphabetized co-authorships over time using a data set which is more comprehensive and diverse than that employed by LT. We utilize data from the economics subject category of the Web of Science (WoS) provided by Clavariate Analytics. Our data set includes papers of the document type 'article' ranging from 1990 to 2013. We collect citations up to the end of 2016. Thus, each article has a citation window of at least three years that allows reliable impact measurements. We make two adjustments to the original data set inasmuch as we keep only those journals that are listed in 2013 in the WoS economics subject category. We therefore exclude journals that have been discontinued or re-classified. Furthermore, we exclude journals with less than 100 listed articles. This lower limit is necessary to achieve sufficient statistical power for the separate regressions for each journal. The final data set consists of 207,159 articles published in 307 journals. Of these articles, 125,559 have at least two authors (61%). Building upon LT, we define three categories of multi-authored papers (strata): (i) all multi-authored articles; (ii) articles with two authors and (iii) articles with more than two authors. The latter two categories together constitute the first.

The left panel of Figure 1 confirms the trend of increasing numbers of authors and a decline in single-authored papers in economics. This has also been documented by Nowell

and Grijalva (2011), Rath and Wohlrabe (2016) as well as Kuld and O'Hagan (2018). Articles with more than two authors have become particularly more prevalent recently.

The alphabetization rate for multi-authored papers is around 70% in our sample (see Table 2) which is similar to the value reported by Waltman (2012) for economics.[1] Table 2 also shows that the alphabetization rate for articles with two authors (roughly 80%) is higher than the overall figure. The right panel of Figure 1 shows the development of alphabetized co-authorships over time, stratified by number of co-authors. The gold standard of alphabetized author order seems to be on the decline, especially since 2005. This holds true more or less for all author number strata. The decrease in alphabetization rate in economics is in line with the development in other subject catogories in science as documented by Waltman (2012).

The overall decline in alphabetized co-authorships appears to be driven by two effects: First, the alphabetization rate for all strata is declining over time, not just for one specific stratum. Second, strata with a lower rate of alphabetization (larger author teams) seem to be gaining in importance. This can be deduced from the strong increase in average authors per article. Despite the declining trend in alphabetization rates, economics still ranks as one of those disciplines where alphabetical author orders are most widespread (Waltman 2012). This is in contrast to other disciplines such as theoretical physics (50%), political science (61%), or statistics (56%). Whereas Waltman (2012) puts the overall alphabetization rate of economics papers at around 72%, our analysis further shows that this value seems to be driven by articles with two authors. Further research will reveal whether this result holds true for other disciplines. The results of Waltman (2012) suggest that there may be other academic fields with similar average numbers of authors to economics and alphabetization shares that are much closer to our estimates of economics articles, but with more than two authors.

Another source of heterogeneity in alphabetization rates is revealed in Figure 2. This

[1] See also Henriksen (2019) for a case study including Danish economists.

illustrates the distributions of average shares of articles with alphabetized co-authors by journal. Much like the historical gold standard of alphabetized co-authorship, this is at best riddled with exceptions. Nevertheless, the kernel density estimation of the distribution reveals a maximum scattered around 90%.

The example of some elite journals commonly referred to as the top 5 (Card and DellaVigna 2013) shows why the phenomenon of alphabetization may be viewed with too much confidence if one focuses only on economics. In these cases, the rates of alphabetic order are consistently higher than average: *Journal of Political Economy*: 83%, *American Economic Review*: 91%, *Econometrica*: 94%, *Quarterly Journal of Economics*: 94%, *Review of Economic Studies*: 96%. These patterns of co-authorship alphabetizations should be subject to cautious examination, especially if they prove to have a meaningful impact on the citation performance of the article.

Table 1: Alphabetical order for articles in economics journals

| | Number of authors | | |
|---|---|---|---|
| | $> 1$ | $= 2$ | $> 2$ |
| Total | 125,559 | 79,280 | 46,279 |
| Percent alphabetical | 70.11 | 79.74 | 53.63 |
| Percent non-alphabetical | 29.89 | 20.26 | 46.37 |

Figure 1: Development of numbers of authors and author shares (left panel) and alphabetization rates (right panel) over time

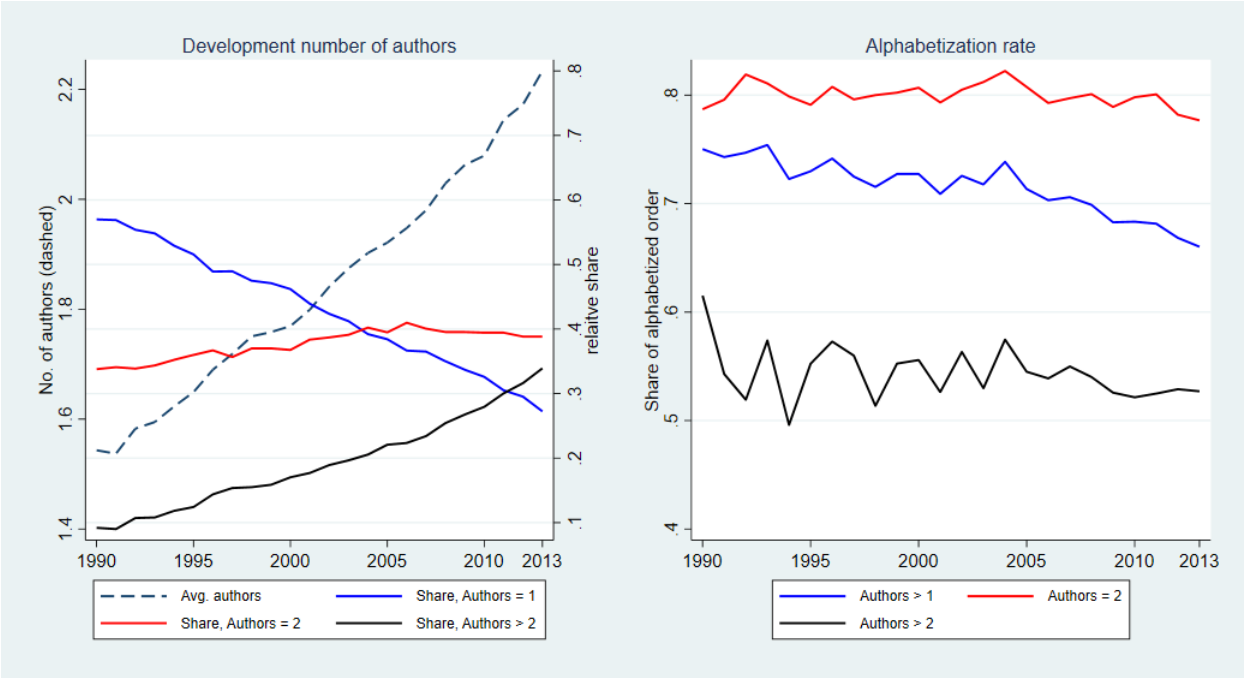
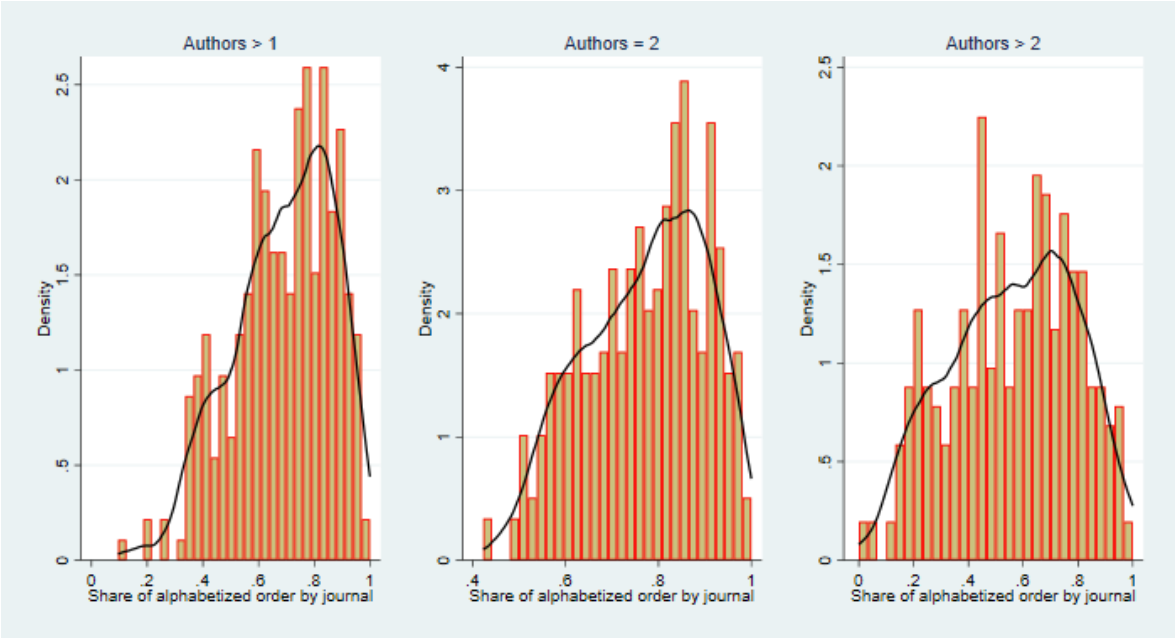



Figure 2: Histograms with kernel estimates of alphabetization rates by author strata across journals



# 3 Empirical approach and results

## 3.1 Empirical approach

In order to test whether alphabetization has a statistically significant effect on citations, we estimate the following model

$$cit_i = \alpha + \beta AB_i + \gamma_1 pages + \gamma_2 pages^2 + \delta_1 age + \delta_2 age^2 + \gamma authors_i + \chi_j + year_t \qquad (1)$$

where $\beta$ is the coefficient of interest. The variable $AB$ is a dummy variable which is 1 if the authorship of an article $i$ is stated in an alphabetical order and 0 otherwise. In case the results of LT hold in general we have $\beta > 0$.[2] We include further variables that might influence the number of citations up to the end of 2016: number of pages, article age (2016–publication year) and the number of authors. These variables have been frequently identified as factors that may influence citations in various studies (see the overview in Tahamtan and Bornmann 2018). The number of pages and article age are also included in the regression model as squared terms to capture non-linear effects. We also account for journal ($\chi_j$) and time ($year_t$) fixed effects. The former accounts for specific journal quality and the latter for citation practices over time. We estimate six different models:

1. Negative binomial regression (NBR) model, where citations are interpreted as counts
2. Basic OLS regression model
3. OLS using the natural log of citations as the dependent variable
4. OLS using the inverse hyperpolic sine (IHS or *asinh*) transformation of citations, similar to log transformation, as proposed by Burbidge, Magee, and Robb (1988) and

[2] The theoretical model by Ong, Chan, Torgler, and Yang (2018) implies that there is no causal effect of alphabetization on citations as team size and ordering a driven by ex-ante matching quality and corresponding selection effects.

put forward recently by Card and DellaVigna (2020) in citation analysis. The formal definition is $asinh(z) = \ln(z + \sqrt{1 + z^2})$. For $z \geq 2$, $asinh(z) = \ln(z) + \ln(2)$, but $asinh(0) = 0$.

5. We define a percentile based indicator, the $PP_{10\%}$, which is a dummy variable that takes the value one when an article belongs to the most 10% cited in a given year $t$ and zero otherwise.[3] We employ a logit model for estimation.

6. We additionally used another percentile based citation impact indicator, the cumulative percentage of the size-frequency distribution of papers ($CP - IN$) proposed by Bornmann and Williams (2020) as the dependent variable. The model is estimated using the fractional logit approach.[4]

The last four approaches account for skewness in the citation distribution which is quite common in science.[5] The six approaches should yield robust results with respect to both the estimation approach and the handling of the dependent variable (citations).

The results of the regression analyses which we present in the following are able to show whether there is a relationship between citation counts and alphabetical ordering of co-authors. It is not possible to reveal causal relationships between both variables.

## 3.2 Basic Results

The results of the regression analysis are shown in Table 2 and are structured as follows. Each panel of Table 2 corresponds to an author number stratification. Each column within a panel then corresponds to one of four specifications of our regression model. In agreement with previous literature (e.g. Gnewuch and Wohlrabe 2017), we obtain the expected sign of

[3] A similar indicator indicator has been used in economics by Bornmann and Wohlrabe (2019).

[4] A similar approach of citation percentile was used in Freeman and Huang (2015) for investigating ethnic co-authorship relationships for US-based authors.

[5] See Seglen (1992) or Seiler and Wohlrabe (2014) for the case of economics.

the coefficients for the explanatory variables and these are statistically significant in almost all cases. For instance, the longer an article or the more authors, the more citations an articles receives. With respect to our variable of interest, we find no statistically significant association of alphabetization on citations across all six regression settings. This generally holds true for multiple authors, two authors and more than two authors. Thus, our findings are in contrast to the results reported in LT.

As the period of time investigated in LT is different and the degree of alphabetization has changed over time (see above), we additionally run the regression analysis for each year separately. The results for each author strata and specification are presented in Figure 3. This shows the estimated alphabetization coefficient ($\beta$) plus the 95% confidence interval bands. If the bands include the zero line, the coefficient is not statistically significant. The apparent statistical insignificance of the coefficient for alphabetized co-authorship for most of the years in our sample confirms the results in Table 2. However, there are some years in the 1990s with statistically significant coefficients that also correlate in part with the time frame in LT. However, the estimated significant coefficients are small. For example, in 1993, the OLS coefficient is around 0.25.[6] Thus, the effect of alphabetized co-authorship on citations is only marginal, even though it is statistically significant in some cases.

In a next step we repeated the analysis for each journal separately as was done for two journals in LT. For this exercise we leave out the logit regression for the $PP_{10\%}$, as many journals do not have any article in the top category. Table 3 shows the relative shares of journals where the alphabetization dummy was statistically significant at different levels across different estimation approaches and degrees of co-authorship. There are journals with statistically significant effects of alphabetization on citations. In all cases the relative shares are somewhat higher than what can be expected from statistical theory.[7] Following

[6] The corresponding coefficient in LT for the *American Economic Review* is about 32.

[7] Based on our sample of 307 journals and given the three significance level 1%, 5% and 10%, one can expect approximately 3, 15 and 30 statistically significant results for the alphabetization parameter respectively.

LT, we take a closer look at the *American Economic Review* and the *American Journal of Agricultural Economics*. In the former case, our results confirm the results of LT. We found a statistically significant coefficient for the NBR and standard OLS with citations as the dependent variable for articles with two authors.[8] In all other specifications and author strata we did not find any statistically significant effects of alphabetization. For the *American Journal of Agricultural Economics*, the results do not point to statistically significant effects across all specifications. Thus, in this case we cannot confirm the results by LT.

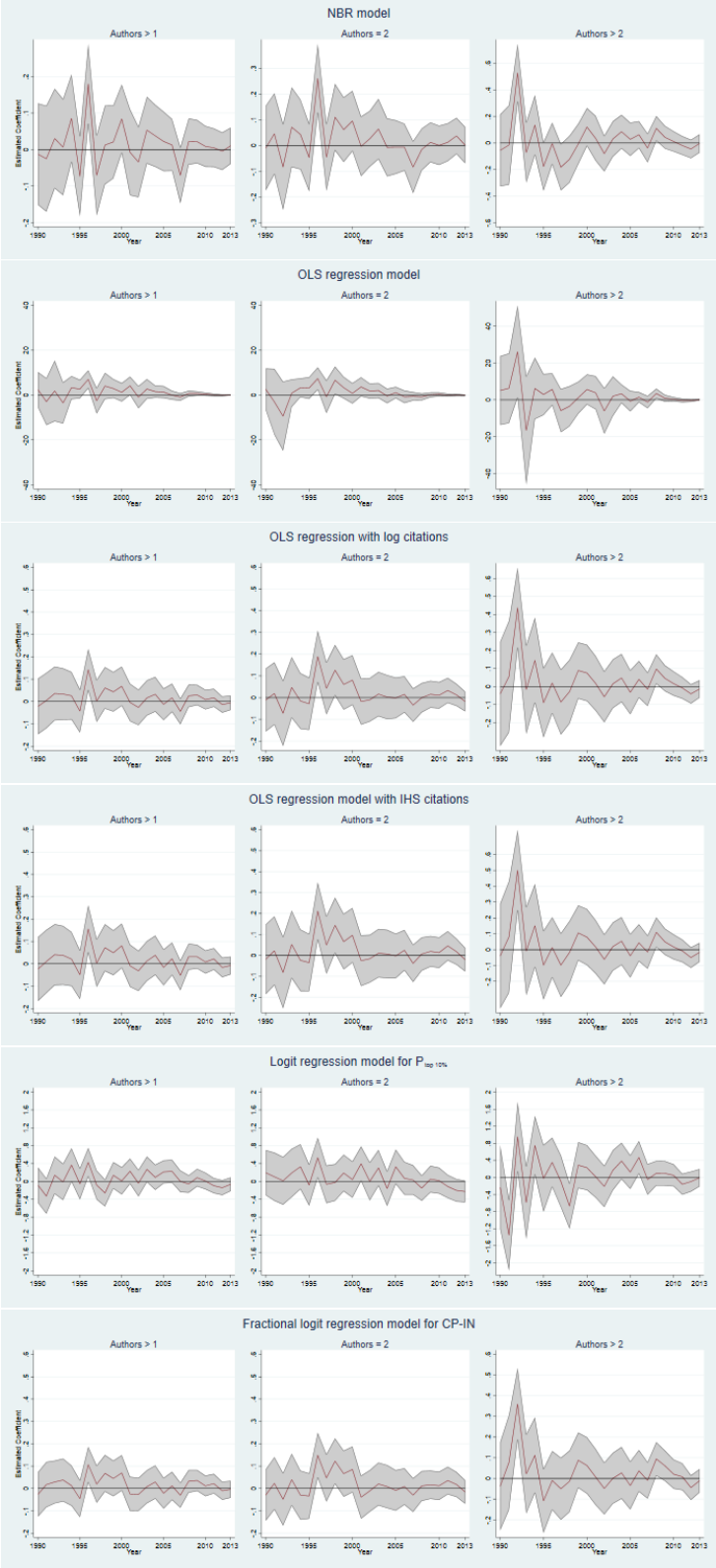
[8]Please note that LT have partially different covariates in their regression models.

Table 2: Regression results stratified by number of authors

| | (1) | (2) | (3) | (4) | | |
|---|---|---|---|---|---|---|
| Estimation approach | NBR | OLS | OLS | OLS | Logit | Fractional Logit |
| Dependent variable | Citations | Citations | Log citations | IHS citations | $PP_{10\%}$ | $CP-IN$ |
| **Authors** $> 1$ | | | | | | |
| Alphabetical order | 0.0013 | 0.0800 | 0.0001 | 0.0009 | 0.0006 | 0.0036 |
| of authors ($1 = yes$) | (0.0103) | (0.3060) | (0.0068) | (0.0078) | (0.0250) | (0.0066) |
| Number of authors | 0.0903*** | 1.807*** | 0.0788*** | 0.0898*** | 0.158*** | 0.0846*** |
| | (0.0047) | (0.1720) | (0.0034) | (0.0039) | (0.0104) | (0.0035) |
| Number of pages | 0.0478*** | 0.9670*** | 0.0416*** | 0.0477*** | 0.0842*** | 0.0404*** |
| | (0.0015) | (0.0488) | (0.0018) | (0.0021) | (0.0037) | (0.0014) |
| Number of pages | -0.0004*** | -0.0041*** | -0.0003*** | -0.0004*** | -0.0006*** | -0.0003*** |
| (squared) | (0.0000) | (0.0011) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Age of article | 0.4450*** | 2.2900*** | 0.3180*** | 0.3830*** | 0.0624 | -0.0276 |
| | (0.0231) | (0.2930) | (0.0140) | (0.0170) | (0.0586) | (0.0160) |
| Age of article | -0.0130*** | -0.0388*** | -0.0096*** | -0.0116*** | -0.00210 | 0.0008 |
| (squared) | (0.0008) | (0.0108) | (0.0005) | (0.0006) | | |
| | (0.0019) | (0.0005) | | | | |
| Time & Journal FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 125535 | 125535 | 125535 | 125535 | 118850 | 125535 |
| **Authors** $= 2$ | | | | | | |
| Alphabetical order | 0.0075 | 0.0586 | 0.0059 | 0.0085 | -0.0053 | 0.0112 |
| of authors ($1 = yes$) | (0.0133) | (0.3960) | (0.0090) | (0.0105) | (0.0355) | (0.0086) |
| Pages of article | 0.0506*** | 0.9530*** | 0.0431*** | 0.0496*** | 0.0882*** | 0.0425*** |
| | (0.0021) | (0.0602) | (0.0031) | (0.0037) | (0.0048) | (0.0020) |
| Number of pages | -0.0004*** | -0.0042** | -0.0003*** | -0.0004*** | -0.0007*** | -0.0003*** |
| (squared) | (0.0000) | (0.0016) | (0.0001) | (0.0001) | (0.0000) | (0.0000) |
| Age of article | 0.4700*** | 1.8600*** | 0.3050*** | 0.3690*** | 0.141 | -0.0388 |
| | (0.0335) | (0.4000) | (0.0191) | (0.0232) | (0.0872) | (0.0215) |
| Age of article | -0.0138*** | -0.0259 | -0.00910*** | -0.0111*** | -0.0045 | 0.0013 |
| (squared) | (0.0011) | (0.0145) | (0.0007) | (0.0008) | (0.0029) | (0.0007) |
| Time & Journal FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 79263 | 79263 | 79263 | 79263 | 73172 | 79263 |
| **Authors** $> 2$ | | | | | | |
| Alphabetical order | -0.0002 | 0.2940 | 0.0006 | 0.0009 | 0.0180 | 0.0001 |
| of authors ($1 = yes$) | (0.0150) | (0.4950) | (0.0104) | (0.0121) | (0.0361) | (0.0104) |
| Number of authors | 0.0709*** | 1.477*** | 0.0604*** | 0.0674*** | 0.130*** | 0.0649*** |
| | (0.0062) | (0.2200) | (0.0048) | (0.0054) | (0.0141) | (0.0053) |
| Number of pages | 0.0443*** | 1.0160*** | 0.0394*** | 0.0447*** | 0.0796*** | 0.0381*** |
| | (0.0019) | (0.0843) | (0.0018) | (0.0021) | (0.0058) | (0.0018) |
| Number of pages | -0.0003*** | -0.0041* | -0.0003*** | -0.0003*** | -0.0006*** | -0.0003*** |
| (squared) | (0.0000) | (0.0018) | (0.0000) | (0.0000) | (0.000102) | (0.0000) |
| Age of article | 0.4270*** | 2.8080*** | 0.3390*** | 0.4060*** | 0.0100 | -0.0077 |
| | (0.0302) | (0.4400) | (0.0207) | (0.0249) | (0.0797) | (0.0241) |
| Age of article | -0.0126*** | -0.0549** | -0.0103*** | -0.0124*** | -0.0008 | 0.0001 |
| (squared) | (0.0010) | (0.0169) | (0.0007) | (0.0008) | (0.0027) | (0.0008) |
| Time & Journal FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 46272 | 46272 | 46272 | 46272 | 42266 | 46272 |

*Notes*: Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Constant always included but not reported

Figure 3: Alphabetization impact over time across regression approaches




Note: Each graphs plots the estimated alphabetization parameter $\beta$ plus the 95% confidence interval bands.

Table 3: Effect of alphabetization on citations across journals

| Estimation approach | Dependent variable | Number of authors $> 1$ | $= 2$ | $> 2$ |
|---|---|---|---|---|
| | **p-value=0.01** | | | |
| NBR | Citations | 3.26 | 4.89 | 5.54 |
| OLS | Citations | 1.30 | 3.26 | 1.30 |
| OLS | Log citations | 1.30 | 0.98 | 1.63 |
| OLS | IHS citations | 1.30 | 0.98 | 1.63 |
| Fractional Logit | $CP - IN$ | 2.28 | 2.28 | 4.23 |
| | **p-value=0.05** | | | |
| NBR | Citations | 10.10 | 12.70 | 13.03 |
| OLS | Citations | 6.19 | 8.14 | 5.86 |
| OLS | Log citations | 6.84 | 5.54 | 7.49 |
| OLS | IHS citations | 7.17 | 5.86 | 7.49 |
| Fractional Logit | $CP - IN$ | 9.77 | 8.47 | 12.38 |
| | **p-value=0.10** | | | |
| NBR | Citations | 17.92 | 18.24 | 19.87 |
| OLS | Citations | 13.68 | 13.36 | 11.73 |
| OLS | Log citations | 13.36 | 12.38 | 13.03 |
| OLS | IHS citations | 13.03 | 11.07 | 13.36 |
| Fractional Logit | $CP - IN$ | 14.66 | 13.03 | 17.26 |

*Notes*: The table shows the relative shares of significant cases of the alphabetization parameter in regression (1) run over each journal for three significant levels.

## 3.3 Accounting for heterogeneity in alphabetization rates across journal quality

Although we account for journal quality in our regression settings our results might be biased or spurious as the alphabetization rate across journals is quite heterogeneous (see Figure 2). Joseph, Laband, and Patil (2005) demonstrate that the probability of alphabetization increases with the publication hurdles, i.e. the reputation of a journal. This implies the authors of alphabetized papers have a tendency of being of a similar and higher quality. On the other hand, non-alphabetization becomes more likely if the quality gap between the

authors gets larger. This is also confirmed by the analysis by Van Praag and Van Praag (2008) who show that a higher inequality of author reputations increases the likelihood of non-alphabetical ordering and vice versa. As a consequence the results found by LT may not generalized as they investigate two top journals.

In order to investigate this issue we define four journal quality tiers. These are categorized by the quantiles across journal impact factors. These impact factors are approximated by the ratio of total citations and the number of articles over the full time span.[9] We now repeated our regression analysis across all four quality tiers.[10] In almost all settings the alphabetization dummy is not significant at all. There is only one exception. In the third quality tier, we find significant results at the 5% level in case of the log and IHS citations as well as the $CP - IN$. This holds for multiple authors in general and the two-author case but not for more than two authors. However, we conclude that our findings are robust with respect to alphabetization rate heterogeneity across journal ranks.

## 3.4 Robustness with respect to intentionally alphabetical ordering

Our analysis neglects one important issue so far, whether the alphabetical ordering is intentional or incidental. Thus, although our results are quite convincing so far, they might not be robust. The ordering of authors can either be alphabetic or based on some kind of merit. This can be due to some member characteristics of the research group as contribution, reputation or hierarchical issues. It could be the case that for an article with two authors the ordering is alphabetical just by chance in case that the first author also contributed more than the second author. Without accounting for this issue the interpretations both of the reported shares of alphabetical co-authorship and our regressions results might be mislead-

[9] These kind of impact factors are also provided on the RePEc website, see Zimmermann (2013) for further details.

[10] In order to save space we do not report the extensive regression results. Details can be obtained from the authors upon request.

ing. In a first step we calculate the share of intentional alphabetical ordering ($\hat{p}$) using the formula given in Waltman (2012) building on Van Praag and Van Praag (2008):

$$\hat{p} = \frac{1}{N} \sum_{i=1}^{N} \hat{p}_i \tag{2}$$

where

$$\hat{p}_i = \frac{AB_i - \frac{1}{Authors_i!}}{1 - \frac{1}{Authors_i!}} \tag{3}$$

$AB_i$ is the dummy variable also used in equation (1) which is 1 if the ordering is alphabetical and 0 otherwise. $Authors_i$ denotes the number of authors of article $i$ and ! the factorial. Waltman (2012) shows that $\hat{p}$ is an unbiased estimator of the average probability of intentionally chosen alphabetical ordering. In Table 4, we compare our empirically observed shares with the estimated ones.[11] As expected the latter ones are smaller than the empirical shares. For all multi-authored papers the share drops form 70% to 55%. As the last two columns in Table 4 show this is mainly due to papers with at least three authors.

Table 4: Comparison of empirical and estimated intentionally alphabetical co-authorship

| | Number of authors | | |
|---|---|---|---|
| | $> 1$ | $= 2$ | $> 2$ |
| Empirical co-authorship in % | 70.11 | 79.74 | 53.63 |
| Intentionally alphabetical co-authorship ($\hat{p}$) in % | 55.02 | 59.47 | 47.40 |

In order to investigate potential consequences for our conclusions based on our regression models we run a simulation. For each model presented in Table 2 based on equation (1) we set for a random selection of articles the alphabetization dummy $AB_i$ from 1 to 0 and run the regression again. Inspired by the results in Table 4 these shares are 10%, 20% and 30%. For each model we run 1,000 regressions.[12] Table 5 shows the results of our simulation

[11] Levitt and Thelwall (2013) provide evidence of intentional alphabetical ordering for other science disciplines.

[12] A similar simulation exercise can be found in Wohlrabe and Bürgi (2021).

exercise. In each case we report the mean of the alphabetization dummy coefficient over all regressions plus the corresponding standard deviation. Additionally, we count the number of statistically significant cases, where we set the significance level at 10%. The comparison of Table 2 with Table 5 shows that the average coefficient for alphabetization shrinks towards zero. The shrinkage increases by decreasing the alphabetization rate. On the other side the standard deviation increases. This holds also true for the number of significant cases. However, the overall number is smaller than what can be expected from statistical theory. Given the significance level of 10% one would expect 100 statistically significant cases. There are two exceptions: the standard OLS case with citations as the dependent variable for articles with more than two authors and the fractional logit regression for $CP - IN$ for two authors.[13] Here, the corresponding numbers are somewhat higher than 100. However, we conclude based on the results in Table 5 that our previous interpretations and conclusions remain strongly valid after controlling for intentionally alphabetical ordering of authors.

## 3.5 Determinants of alphabetization

We now repeat the analysis of Brown, Chan, and Chen (2011) and asked whether the number of authors affects the probability of alphabetical ordering. We estimated a linear probability model using OLS and a logit regression by including the number of authors and pages as explanatory variables. Table 6 shows the corresponding estimation results. In line with Brown, Chan, and Chen (2011) the results reveal that more authors increase the likelihood of authors being ordered *non*-alphabetically. It confirms also the results of Torgler and Piatti (2013) who investigated this issue for the *American Economic Review*.

[13] In case of the fractional logit the model estimation does not always converge or find a maximum. In these cases we stopped the estimation after 300 iterations and retained the resulting regression results.

Table 5: Simulation results

| | Authors | >1 | | | 2 | | | >2 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Estimation approach | Share | Mean | Stand. dev. | Sign. Cases | Mean | Stand. dev. | Sign. Cases | Mean | Stand. dev. | Sign. Cases |
| NBR Citations | 10% | 0.0007 | 0.0060 | 33 | 0.0047 | 0.0085 | 98 | -0.0002 | 0.0073 | 6 |
| | 20% | 0.0005 | 0.0072 | 57 | 0.0035 | 0.0096 | 127 | -0.0004 | 0.0094 | 21 |
| | 30% | 0.0002 | 0.0078 | 66 | 0.0026 | 0.0101 | 118 | -0.0005 | 0.0111 | 43 |
| OLS Citations | 10% | 0.0605 | 0.2148 | 53 | 0.0404 | 0.2806 | 49 | 0.2478 | 0.3431 | 117 |
| | 20% | 0.0528 | 0.2529 | 85 | 0.0259 | 0.3137 | 80 | 0.2339 | 0.4373 | 139 |
| | 30% | 0.0502 | 0.2749 | 101 | 0.0226 | 0.3381 | 90 | 0.2209 | 0.5100 | 159 |
| OLS Log citations | 10% | 0.0001 | 0.0035 | 9 | 0.0042 | 0.0049 | 103 | 0.0004 | 0.0050 | 4 |
| | 20% | 0.0001 | 0.0041 | 31 | 0.0031 | 0.0056 | 126 | 0.0006 | 0.0066 | 35 |
| | 30% | 0.0001 | 0.0047 | 60 | 0.0025 | 0.0061 | 140 | 0.0007 | 0.0077 | 55 |
| OLS IHS citations | 10% | 0.0007 | 0.0040 | 16 | 0.0060 | 0.0057 | 143 | 0.0006 | 0.0058 | 3 |
| | 20% | 0.0006 | 0.0048 | 39 | 0.0045 | 0.0064 | 148 | 0.0007 | 0.0075 | 33 |
| | 30% | 0.0005 | 0.0054 | 69 | 0.0036 | 0.0070 | 164 | 0.0008 | 0.0088 | 55 |
| Logit Top 10% | 10% | 0.0005 | 0.0133 | 15 | -0.0035 | 0.0200 | 15 | 0.0147 | 0.0172 | 43 |
| | 20% | 0.0003 | 0.0156 | 47 | -0.0025 | 0.0215 | 36 | 0.0119 | 0.0227 | 93 |
| | 30% | 0.0007 | 0.0170 | 77 | -0.0018 | 0.0226 | 63 | 0.0112 | 0.0255 | 110 |
| Fractional Logit $CP-IN$ | 10% | 0.0031 | 0.0034 | 75 | 0.0074 | 0.0046 | 299 | 0.0003 | 0.0048 | 5 |
| | 20% | 0.0022 | 0.0041 | 112 | 0.0053 | 0.0054 | 254 | 0.0002 | 0.0064 | 28 |
| | 30% | 0.0018 | 0.0045 | 119 | 0.0043 | 0.0055 | 212 | 0.0000 | 0.0073 | 27 |

*Notes*: This table reports simulation results where for each estimation approach the mean and the corresponding standard deviation over 1,000 regression runs. In each case we set 10%, 20% or 30% of articles the alphabetization dummy to zero. For counting the significant cases we set the threshold at 10%.

Table 6: Regression results: determinants of alphabetization

| | (1)<br>OLS | (2)<br>Logit |
|---|---|---|
| Number of pages | 0.0003613 | 0.0035777 |
| | (0.0005082) | (0.0029066) |
| Number of pages (squared) | 0.0000121 | 0.0000805 |
| | (0.00000984) | (0.0000578) |
| Number of authors | -0.1106878*** | -0.8186007*** |
| | (0.0027538) | (0.010939) |
| Time and journal fixed effects | ✓ | ✓ |
| $N$ | 125,535 | 125,481 |

*Notes*: Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# 4 Discussion

There is no doubt as to the importance of citations. Citations promise to be an objective, long-term measure of a researcher's impact on the scientific discourse channeled by academic journals, as well as a proxy for the quality of precisely these journals. The important role of citations for both authors and journals naturally raises the question of what determines the number of citations per article? The quality of research contributions is an appealing answer. Bibliometric research, however, found various other potential factors of contextual (author or journal quality) and technical nature, such as title characteristics (Gnewuch and Wohlrabe 2017) and subject category (Medoff 2003). Bornmann and Daniel (2008) and more recently Tahamtan and Bornmann (2019) provide an overview of citing behavior and factors that potentially influence citations. Laband and Tollison (2006) found that with up to two authors - alphabetization also pays off potentially in the form of more citations. The authors conclude that a team size of two is optimal. This is in line with the empirical fact that sole-authored articles in economics are in decline whereas multi-authored articles become more and more popular. This fact has been revealed, for instance, by Nowell and Grijalva (2011)

and more recently by Rath and Wohlrabe (2016) as well as Kuld and O'Hagan (2018). Huang (2015), based on a large set of articles from the WoS, estimated that papers whose authors' surname initials appear earlier in the alphabet receive more citations than those with initials later in the alphabet. Thus, the results suggest a new dimension that might be considered when choosing the order of authors.[14] In contrast, Abramo and D'Angelo (2017) found no effect of the surname focusing on the individual instead on the paper level.[15] Brogaard, Engelberg, Eswar, and Van Wesep (2020) provide causal evidence that articles whose first authors are more famous than the other authors receive more citations compared to those papers where the famous author is listed second or third. The finding that authors listed earlier in the alphabet may be favored in terms of academic rewards has been confirmed by several other authors: working at top economic departments (Einav and Yariv 2006 or Efthyvoulou 2008) or publishing in mainstream economic journals (Van Praag and Van Praag 2008). Maciejovsky, Budescu, and Ariely (2009) show experimentally that scientists assign higher credits to first authors independently whether they were ordered alphabetically or not. This phenomenon has been labeled as 'alphabetical discrimination'. Weber (2018) provides a survey of empirical evidence with respect to alphabetical ordering especially in economics. It has also been shown that scientists strategically react to these empirical findings. Authors with surnames late in the alphabet work less in large teams (Kadel and Walter) or 2015. Ong, Chan, Torgler, and Yang 2018 show theoretically and empirically that there is a tendency that authors with late surnames to write single-authored papers especially for best ideas. Efthyvoulou (2008) found that some authors manipulate their name to move upwards in the alphabet. Li and Yi (2021) show how surname initials affect labour market decisions of Chinese economists. Weber (2018) also provides a literature survey on the strategically reaction to alphabetical discrimination.

[14] Arsenault and Larivière (2015) document also such findings based on much larger sample but do not report any size effects and evidence on statistical significance.

[15] See Weber (2017) for critical review on this article.

This article re-investigates the issues raised by LT using a much larger data set consisting of more than 120,000 multi-authored articles published in 307 journals from the economics category in WoS. In the first part of the study we show that the alphabetization rate in economics has declined since the early 2000s. This is in contrast with the prediction of Engers, Gans, Grant, and King (1999) who postulated a theoretical equilibrium of all authors playing an "alphabetized order strategy". In the second part we use six different regression settings to answer the question whether the order of authors affect the number of citations of an article. We do not find any statistically significant effects of alphabetization across all settings. Our findings thus directly contradict the conclusions in LT. However, our analysis confirms the finding of LT for the *American Economic Review*: articles with two alphabetically ordered authors obtain statistically significantly more citations than articles with alphabetically unordered authors. This relationship also holds true for a few other journals. Our analysis shows that in the light of rising co-authorship (in economics), the ordering of authors does not matter, at least not for citations. Ray and Robson (2018) proposed an algorithm for random co-authorship listing. If this would be adopted by all journals, an analysis like ours should become obsolete in the future.

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