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The Benefits of being Economics Professor A (and not Z)

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ABSTRACT

The Benefits of Being Economics Professor A (and not Z)

Alphabetic name ordering on multi-authored academic papers, which is the convention in the economics discipline and various other disciplines, is to the advantage of people whose last name initials are placed early in the alphabet. As it turns out, Professor A, who has been a first author more often than Professor Z, will have published more articles and experienced a faster growth rate over the course of her career as a result of reputation and visibility. Moreover, authors know that name ordering matters and indeed take ordering seriously: Several characteristics of an author group composition determine the decision to deviate from the default alphabetic name order to a significant extent.

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1. INTRODUCTION

The performance measurement of individual academic output, i.e. research publications, has become a profession by itself. The resulting measures form the basis for academics' salary increases, promotions, outside offers, and reputations (Moore et al, 2001). An explicit factor in these performance measurement systems is the number of co-authors on the paper.[2]

An implicit factor one believes to affect individual academic performance is the author's rank in the author group of a multi-authored paper, even if the convention in the discipline is alphabetic name ordering as is the case in economics, the discipline we study. Approximately 85% of multi-authored economics papers are observed to use alphabetic name ordering.[3]

First authorship would entail certain benefits and count heavier than second authorship. First, non-economists from disciplines that use merit based name ordering –to be defined precisely below- will perceive 'first authors' in economics journals as the authors with the highest contribution. Second, citation indices have for a long time only counted names of first authors. This implies an additional benefit attached to being the first author, since the number of citations is a common performance measure. Third, citations within articles, which clearly contribute to someone's reputation and visibility, are shortened "first author et al." as soon as there are more than two authors. Finally, visibility is also constrained for others than first authors in frequently used search engines such as *Econlit*: It merely reveals the name of the first author for articles with more than three authors.

Hence, alphabetic name ordering would be to the disadvantage of authors whose names begin with a *Z*.[4] The first aim of this paper is to measure the magnitude of such an effect in the economics discipline.[5] And if the effect is sizable, do economists perceive name order selection for multi-authored papers as a deliberate choice?

Basically two name ordering strategies can be used. The first is the alphabetic strategy, while the second is non-alphabetic. We assume that non-alphabetic name ordering will typically be the result of uneven contributions, differences in hierarchical positions or in academic reputations between co-authors. We call the last ordering merit-based, where "merit" refers to all characteristics of an author group (contribution, academic reputation, or hierarchical positions) that lead to the group's decision to use a non-alphabetic name ordering. We denote the alphabetic strategy by α, and the alternative by $\overline{\alpha}$.

The outcome of 'merit-based' may be an alphabetical order as well. Looking at a sample of two-authored articles by *A* and *B*, it is obvious that if all authors followed α, we would find that the fraction of *AB* articles is 100%. In the other extreme case, in which all authors would follow the merit strategy, we would find a fraction of 50%, assuming independence between last names and merit. In practice, part of the *AB*- papers is the product of the merit-strategy, while the other part is a result of the alphabetic strategy. Let p_α denote the chance that the alphabetic strategy is used. Then in the case of two authors, the chance of finding an alphabetical ordering $P(AB) = p_\alpha + (1 - p_\alpha) * 0.5$. From the observed $P(AB)$ we may assess the latent chance p_α by

(1) $p_\alpha = 2*P(AB)-1$

The chance $P(AB)$ is the sum of the probabilities of using the alphabetic strategy and the probability of getting the alphabetic result, while embracing the merit strategy. Likewise, for *n* authors the relationship between the observed frequency of alphabetic name ordering and the frequency of following an alphabetic strategy is:

(2) $P(AB .. N) = p_\alpha + (1- p_\alpha)*1/n! \rightarrow p_\alpha = \dfrac{P(AB...N) - \frac{1}{n!}}{1 - \frac{1}{n!}}$

The larger *n*, the smaller is the difference between the observed alphabetic fraction and the fraction of users of an alphabetic strategy.

The second aim of the paper is to answer the question: What are the characteristics of the author group that influence their choice between name ordering strategies α or $\overline{\alpha}$?

Thus, our paper aims at making two contributions. First, the effect of alphabetic rank of an economist's last name on individual productivity is measured. Second, we estimate the determinants of the (only partially observed) choice of author groups to deviate from an alphabetic name ordering strategy. The second analysis is novel. The first, i.e. measuring the effect of last names on productivity, has also been performed by Einav and Yariv (2006), using different measures of individual productivity and a more selected sample of economists.[6]

The paper proceeds as follows. Section 2 describes the sample and how it was obtained. Section 3 deals with the effect of alphabetic name rank on individual academic output. Section 4 focuses on the determinants of following a merit strategy by author groups and thereby diverging from the alphabetic name ordering convention. Section 5 concludes that alphabetic name ordering is to the advantage of people whose last name initials are placed early in the alphabet. Moreover, authors know that name ordering matters and indeed take ordering seriously: Several characteristics of an author group composition determine the name order decision to a significant extent.

2. DATA

The sample we collected consists of all regular articles published in the period 1997-1999 in 11 mainstream economics journals. They are listed in Appendix Part A, where we also elaborate on the criteria used for selecting journals and articles. The resulting *articles* database consists of 2,311 articles. Table 1 shows that, consistent with Hudson's findings, 55% of these 2,311 are multi-authored leading to a database of 1,278 multi-authored articles (In Appendix Part A we comment on the variables included in this database). The vast majority of multi-authored papers, i.e. three quarter, is written by two authors, whereas 22 percent is written by three authors. The percentage of articles written by more than three authors is smaller than four. The observed percentage of alphabetic name ordering in the entire set of multi-authored papers is 88%, translating, by means of (3) into a fraction using an alphabetic strategy, p_α, of 80%.[7]

-Insert Table 1 here-

The *authors*' dataset contains author specific variables for each of the 2,103 different authors of the 1,278 multi-authored articles (see Appendix Part B for the definitions, sources and descriptive statistics of these variables). Besides their name, gender, institute affiliation and geographical location, the 'scientific age' and 'scientific weight' of each author have been assessed. An author's 'scientific age' has been calculated as the year 2002 minus the year of the first publication in a journal included in the SSCI. The median (mean) value is 13 (14.7) years. The variable 'scientific weight' denotes the *number* of articles the author has published since 1969. 'Scientific weights' vary from 1 to 175. The median (median) value is 14 (20) articles. The correlation between scientific weight and age is 66.8%.

3. EFFECT OF ALPHABETIC NAME RANK ON INDIVIDUAL OUTPUT

We wish to measure whether having a name ranked earlier in the alphabet contributes to academic performance. To this end, we will estimate two performance measures and include the relative alphabetic rank of an author as a potential determinant. The two performance measures are: (1) an author's total number of publications in refereed economics journals, i.e. "scientific weight" and (2) an author's scientific output per year, i.e. "scientific weight" divided by "scientific age".[8] We estimate the effect of the alphabetic position of an author's last name on both performance measures, while controlling for potential productivity related factors such as gender, geographical location and whether the author works in or outside academia.[9]

Two assumptions are made. First, authors don't seek co-authors based on their name (occurring later or earlier in the alphabet than their own name). This assumption must on average be true since, in the case of two authors, one will always have a higher ranked name than the other. Second, the size of the author group is independent of the authors' alphabetical positions. For instance, we assume that Z-authors do not prefer single authorship to joint authorship because that would guarantee being 'first author'. The latter assumption has been investigated and could not be rejected (see Appendix Part C).

Note that we look at the productivity effect of name position in the alphabet, instead of actual first authorships. The effect of actual first authorships (indeed the author with the lowest ranking letter in 88% of cases) would most probably be biased due to endogeneity, since a deliberate decision, probably based on productivity, is involved here. Alphabetic name rank can be considered a qualified and valid instrument of the probability that one is first author, given the alphabetic ordering convention.

Suppose we would indeed find that scientific productivity is higher for individuals whose last names occur earlier in the alphabet. Could we then conclude that this productivity effect is the result of increased reputation and visibility? If so, we would expect this fact to arise late, but not early, in an economist's career. Thinking about reputations and how they are formed, we can hardly expect differences in reputation (and thereby scientific output), caused by the effect of name ordering, amongst authors who have written zero or few articles before. None of them have had any chance to build a reputation and visibility, whether they are *A* or *Z* starters, since it takes time to build a reputation. Including these debutant authors in our sample therefore generates noise when measuring the effect of reputation (through name ordering). Therefore we consider two samples: (1) economists who have at least one publication in a top or middle class economics journal, and (2) economists who have at least 15 publications in refereed economics journals, thereby being above median performers in our sample. [10] For similar reasons, Einav and Yariv (2006) have even restricted their sample to top economics departments in the United States.

Another way of testing if people who are likely to be first authors get differential credit when publishing more is to measure if the effect of scientific age on annual productivity is larger for economists whose names are in the beginning of the alphabet. If new publications are driven by first-authorships of previous papers, then *A*'s should see a faster growth than *Z*'s.[11]

Table 2, Panel *A*, shows the estimation results where the indicator for academic performance is scientific weight (column I) and annual scientific productivity (column II).

-Insert Table 2-

The first two rows contain the key variable of interest, i.e. (log) "letter". This variable is based on the cumulative distribution of first letters of authors in the multi-authored articles sample. For the i^{th} letter we define "letter" by $100.[\frac{1}{2}(F(i)+F(i-1))]$ where $F(.)$ stands for the empirical distribution function of the alphabetic frequency distribution. It ranges from 3.76/2 for authors whose names start with an A to (98.43+100)/2 for authors whose names start with a Z. Thus, the variable indicates where one stands in the name distribution of economists. The first two columns (and rows) in the table show that there is no significant effect of alphabetic name rank, neither on scientific weight, nor on annual productivity.

The effects of the control variables are notable. Not surprisingly, scientific age is a major determinant of publications: People who are one year further in their careers, have on average 1.56 more publications (see also Maske et al., 2003). Scientific age is omitted as a control variable in the productivity equations because it is the denominator of the dependent variable. In line with Maske et al. (2003), females publish less, both in total and per year. They have on average 3.7 fewer publications than men, whereas their annual productivity is 0.42 articles lower. The first two equations do not show any evidence that authors from the US are more productive than their European colleagues. Asian economists have an almost significantly lower annual production. Academic affiliation has the expected effect: People whose main affiliation is outside the university have a significantly lower scientific weight (-2.75) and annual productivity (-.23).

The distribution of scientific weight has a few observations with very high values. Therefore, next to traditional OLS, we applied two common procedures to minimize the effect of outliers: median regressions (columns III and IV) and some log-transformations (columns V and VI).

The effect of someone's position in the alphabet remains unaffected and insignificant. Our preliminary conclusion still stands. The effects of the control variables are somewhat affected. We now see that US authors have more publications and are more productive per year than Europeans. Asian authors perform slightly worse.

As was discussed, it may be the case that being an *A*-author or a *Z*-author will only start to affect scientific production after the first couple of publications (most likely as a first author for *A*-authors and as a last author for *Z*-authors). Therefore, the earlier analysis in Panel *A* is repeated for the group with a *higher than median* scientific weight only (cf. the restriction by Einav and Yariv to the top five or ten schools).[12] Panel *B* in Table 2 shows the results. If the letter rank were irrelevant to building a reputation, it would have no effect in this sub-sample either.

Interestingly, columns III to VI, in which we account for the non-normal distribution of the dependent variables, all show a significantly negative effect of "letter" on scientific performance, indicating a reputation advantage of *A*-professors over *Z*-professors, resulting in an increased scientific output of 3.4 articles ((100+98.4)/2-3.76/2)*0.035) and an 0.16 (97.3%*0.0017) articles higher annual productivity. Columns V and VI show that a one percent lower letter-ranked name increases both total and annual output by 3.3 percent points. The table shows furthermore that various determinants of scientific standing have ceased to explain the within-sample variation in academic output for the group of relatively successful economists. The only consistent determinants of *scientific weight* are 'letter' and 'scientific age'; the unique determinant of *annual productivity* is 'letter'.

The result is consistent with Einav and Yariv (2006), who find a significant correlation between last name ranking and tenure at the top 5 and top 10 economics departments in the US, but the effect becomes insignificant when they extend their sample and include lower ranked economics departments (to 20 or top 35).[13] Hence, our findings are remarkably in line with these of Einav and Yariv: The relationship between name rank and productivity is only significant *given* a sample of highly productive economists. One might think that we introduce a bias by selecting on the variable to be explained, as is the case when a wage equation estimated for workers is extrapolated to predict market wages for unemployed workers. However, given that we do not extrapolate our findings to a sample consisting of all authors, the prolific and the non-prolific ones, our estimated regression equation -valid for the sub-sample-, is not biased.

The second test of the relevance of letter rank for academic productivity (growth) is assessing whether the effect of 'scientific age' on productivity is larger for lower letter-ranked names. This would imply that scientific productivity grows faster for *A*-authors than for *Z*-authors, because *A*-authors have been more visible on previous publications and have therefore built more reputation that, in turn, increases productivity. Hence, regressions are run with (log) annual productivity as a dependent variable and all the independent variables included in Table 2, where we add a cross-term of the variables (log)letter and (log) scientific age (both demeaned) whose coefficient measures the effect of interest. In addition, we control for (log) scientific age; this is required to estimate the cross-effect consistently. Table 3 shows the results. In both specifications, the relevant coefficient has the expected sign, and is marginally significant, implying that the scientific productivity of lower letter-ranked economists grows faster when they get older than the scientific productivity of higher letter-ranked economists.

Given these results the obvious question is if there should not be a correction for the effect of alphabetic name rank on academic output. Our estimates in the last column of Table 2, Panel *B*, indicate that a *Z*-author would deserve a 16% premium on his observed weight as compared to an *A*-author. This is a non-negligible correction.

-Insert Table 3 here-

4. NAME ORDERING STRATEGIES BY AUTHOR GROUPS

The effect of name ordering on individual productivity is sizeable. We have shown this by using a qualified and valid instrument of the likelihood of appearing as a first author on a paper, i.e. alphabetic name rank. Thus, the next question is: Do economists perceive name order selection for multi-authored papers as a deliberate choice? What are the characteristics of the author group that determine whether we observe alphabetic or merit name ordering?

Individual contributions to co-authorships are unobserved: Truthful statements on this delicate matter are difficult to collect. Therefore, we assume that the unequal distribution of contributions is a function of relevant observable aspects of inequality between authors of a specific article *m*. There are several relevant dimensions: inequality in *scientific weight*; inequality in *scientific age;* and finally inequality in affiliation, i.e. whether some (but not all) co-authors have a non-academic affiliation (often leading to severe time restrictions).

We distinguish *k* aspects and denote those inequalities for article *m* by $\sigma_{m1},...,\sigma_{mk}$, respectively. An over-all author inequality is defined by

$$(3) \qquad S_m = \sum_{1}^{k} \beta_j \sigma_{mj}$$

where the β_j's, to be estimated, represent the relative weights of the various inequality aspects.

We assume that the choice for a non-alphabetic name ordering may be described by a hurdle model, that is, it is chosen if the overall- inequality between authors is too conspicuous to ignore, i.e., if

$$(4) \qquad S_m = \sum_{1}^{k} \beta_j \sigma_{mj} > \gamma$$

Otherwise, name ordering is alphabetic.

It is conceivable that the level of the hurdle itself varies with group characteristics, other than the inequalities amongst authors captured in $\sigma_{m1},...,\sigma_{mk}$. For instance, a group of, on average, older and more settled authors might be more indifferent towards applying the merit strategy and therefore applies a higher hurdle γ. In short, we make γ flexible and we rewrite the inequality above as:

$$(5) \qquad S_m = \sum_{j=1}^{k} \beta_j \sigma_{mj} > \gamma_0 - \sum_{i=1}^{l} \gamma_i x_{mi}$$

where the x_i stand for other group characteristics *i*, such as the *average* scientific weight and average (scientific) age of the author group; the average alphabetic position, since authors whose names all appear early in the alphabet may apply a higher hurdle than authors whose names appear, on average, later in the alphabet and who will have little chance in general to be a first author; inequality in alphabetical position, since the hurdle might be higher, the larger the difference in alphabetic positions is; nationality, as standing for differences in publication customs; and, gender. Moreover, the hurdle might depend on the extent to which a publication counts for someone's academic merit. The vector x therefore also includes the impact factor of the journal and the number of pages of the article. Finally, the hurdle might differ between occasional author groups and longer-term combinations of authors. We would think that occasional groups of authors would rather follow the default strategy, whereas longer-term relations would alternate their names and therefore deviate from the alphabetic order more easily. Conflicts can be solved in a repeated game, by making promises (or threats) about name order in the next period.

We rewrite the inequality above in the usual Probit-format such that the coefficients β and γ can be estimated, i.e., the determinants of non-alphabetic name ordering strategies. Since the difference between the observed behavior -*P(AB)*- and its underlying name ordering strategy -p_{α}- depends on the number of authors (see equation (2)), we estimate the resulting equation separately for the samples of two-authored and three-authored articles. We shall also estimate the equation for the entire sample of multi-authored papers and control for the number of authors. Since a larger number of authors leads to a lower probability of an unintended alphabetic name order, the likelihood of alphabetic name ordering is expected to decrease in the number of authors.

The dependent dummy variable "name order" in this regression equals 1 when a group of authors deviates from alphabetic order, whereas it is zero when they order their names alphabetically. The exact definitions of the independent variables, i.e. the variables $\sigma_{m1},...,\sigma_{mk}$ and the vector x, are provided in Part D of the Appendix.

Table 4 shows the estimation results. For continuous variables they represent the marginal effect of a one percent point change in the regressor (evaluated at their mean values) on the probability of observing a non-alphabetic outcome. For dummy variables the entries in the table denote the effect of changing the dummy value from zero to one. Equations I to III show the results for the entire sample of multi-authored articles, while controlling for the number of authors. Due to the high correlation between scientific age and scientific weight, we present three sets of results, based on: (I) Inclusion of both (log) age and (log) weight characteristics, (II) Inclusion of (log) weight characteristics only, (III) Inclusion of (log) age characteristics only. The differences are minor. Equation IV re-estimates Equation I on the 75% sub-sample of two-authored articles, whereas equation V does so for the 22% sub-sample of three-authored articles.[14]

-Insert Table 4-

In all specifications, at least one of the inequality variables significantly and positively affects the probability to observe a non-alphabetic name ordering, as was expected. Equation II shows that an increase in the standard deviation of the weights of the authors by one percent point increases the probability of observing a non-alphabetic ordering by 8%. Likewise, equation III shows that increasing the standard deviation of scientific age by one percent would increase the probability of observing a non-alphabetic ordering by 5%. These effects are significant and substantial.[15] Differences within author groups in terms of affiliations (academic versus non-academic) do not generate any significant effect.

The hurdle turns out to be affected significantly by some of its potential determinants. Again, focusing on the second and third equations, we see that the average scientific age and weight of the author group both affect their decision to deviate from an alphabetic name order negatively.[16] As we expected, more experienced groups of authors with more publications are less inclined to deviate from the alphabetic name ordering convention. The table reveals that the choice of whether to include age and/or weight characteristics does hardly affect the remaining coefficients. The discussion of these estimates shall therefore be based on the first equation only.

The effect of the average position of author names in the alphabet is significant and as expected: *XY(Z)*-authors apply lower hurdle rates and use a non-alphabetic name ordering more often than *AB(C)*-authors. A larger standard deviation of the letter positions of the authors has a significantly negative effect on the use of a non-alphabetic name order: The closer the letters of the author group are to each other in the distribution of names, the higher the likelihood of observing a non-alphabetic ordering outcome.

The impact figure of a journal has no effect on the usage of alphabetic name ordering. Whereas Joseph et al. (2005) find that the occurrence of alphabetic name ordering is higher in a set of three top journals than in a set of three second tier journals, we find no such effect using a more continuous measure of journal quality. However, the number of pages of the publication impacts name ordering: Longer articles, that have a more powerful effect on the author's career, increase the probability of an alphabetic name ordering. A ten pages longer article than average has a three percent higher probability of alphabetic name ordering.[17]

For occasional author groups we do not observe different name ordering outcomes than for long-term author teams. This result is against our expectation that repeated author groups will deviate somewhat more easily from alphabetic name ordering. Finally, the effects of geographical location and the presence of a female in the author-group are statistically insignificant for the explanation of name order strategies. Moreover, as expected, the number of authors affects the probability of observing alphabetic name ordering negatively.

5. CONCLUSION

Several explicit factors are accounted for in the performance measurement systems used for academics. Other, more implicit, factors might also lead to better academic performance. Alphabetic name rank might very well be such an implicit factor.

The first objective of this paper was to establish whether an economist's academic performance is affected by alphabetic name rank, given the default alphabetic strategy. Indeed, we find significant effects of the alphabetic rank of an economist's last name on scientific production, given that an author has already a certain visibility in academia. Another demonstration of this phenomenon is that the growth rate of an economist's number of publications increases marginally faster over the years for economists whose names rank lower in the alphabet. Being an *A* author and thereby often the first author is beneficial for someone's reputation and academic performance. Hence, name ordering is a strategic decision.

The paper's second aim was to evaluate if authors know that name ordering matters and consequently take ordering seriously. This turned out to be the case: Several characteristics of an author group composition determine the decision to deviate from the default alphabetic name order significantly. One group of such characteristics captures the effect of inequality of merits amongst authors in a group. Increased inequality increases the likelihood of using a merit strategy rather than an alphabetic strategy. The hurdle level that author-groups use for determining whether to deviate from alphabetic name ordering depends on author group characteristics, such as the average scientific standing of the group and the distribution of their names in the alphabet. Name ordering turns out to be not random.

Our findings suggest that there is room for a correction method where individual performance measures are corrected for the advantage or disadvantage of being situated in the vanguard or the rearguard of the alphabet, given the convention of alphabetic name ordering. An alternative way of terminating this practice leading to discrimination against *Z* authors is that journal editors take (random) name ordering decisions. And, the fact that they do should then be public information.

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Appendix

A. Journal and article selection

The articles sample consists of all regular articles published in the period 1997-1999 in the following 11 journals: (1) American Economic Review; (2) Economica; (3) Economic Journal; (4) European Economic Review; (5) International Economic Review; (6) Journal of Economic Behavior and Organization; (7) Journal of Economic Perspectives; (8) Journal of Economic Theory; (9) Journal of Political Economy; (10) Quarterly Journal of Economics; and (11) Review of Economic Studies.

These eleven journals have been selected for their general character, and their mix between European and American origin. Moreover, the selected set of journals includes both top and middle-class journals and they do not impose a specific (alphabetic) author ordering. Three years have been selected to obtain a large enough sample of multi-authored articles. Book reviews, notes, comments as well as papers and proceedings issues are excluded from the sample.

The resulting *articles* database of 2,311 articles is selected from the digital database "Web of Science" (*WOS*). For each of the 1,278 multi-authored articles, the following characteristics are included in the database: (1) Title; (2) Author names; (3) Number of authors; (4) Journal name and its impact score[18]; (5) Year and journal issue; (6) Number of pages; (7) Name ordering (alphabetic or not); (8) Number of previous joint publications (in any refereed journal)

B. Author selection and author-related variables

The *authors*' dataset contains author-specific variables for each of the 2,103 different authors who have published the 1,278 articles in the articles database. The following author-specific variables are included: (1) Name; (2) Gender; (3) Type of institution of main base (university or not); (4) Geographical location of main activities (US/Europe/Asia/Other); (5) 'Scientific age' (number of years since first publication in any journal with impact factor)[19]; (6) 'Scientific weight' (Number of publications in journals with an impact factor since 1969).

The values of each of these author-specific variables have been calculated based on *Econlit*, which includes publications beginning in the year 1969.[20] An author's gender was identified based on first names.[21]

89% of the authors are male. 90% of the authors are mainly affiliated with a university.[22] For the geographical location of the institution that an author is affiliated with, we distinguish between the US, Europe, Asia and other. 57% of the authors are US-based, 33% Europe based and 4% Asia-based. The remaining 6% work elsewhere.[23]

An author's scientific age has been calculated as the year 2002 minus the year of the first publication in a journal included in the SSCI (source: *Econlit*). Unfortunately, the "scientific age" variable had to be truncated at 33 since tracing back publications before 1969 was impossible. This may lead to an underestimate of the scientific age variable for a maximum of 3.4% (72) of the authors in the sample, i.e. the authors who were active in 1969 already.[24]

The variable "scientific weight" denotes the number of articles the author has published since 1969. The source *Econlit*, however, spells out the names of at maximum three authors and only mentions the name of the first author of articles written by more than three authors. Consequently, an author's track record according to *Econlit* is the sum of the number of articles (s)he has written with one or two co-authors and the number of articles (s)he has written as first author with more than two co-authors. This leads to an under-estimate of the track record of authors who where not the first author in an author group larger than three. The majority of these authors will have last names starting with letters late in the alphabet, given the alphabetic convention, resulting in a positive association between a lower ranked last name and scientific weight. To circumvent such a bias, the "scientific weight" calculation includes articles with three authors or less and excludes all articles written by more than three authors.

C. Test of Assumption 2: Independence of author group size and authors' name rank

Table A Distribution of alphabetical ranking of author names

	Authors with co-authors			Authors without co-authors		
Ranking	Frequency	%	Cum. perc.	Frequency	%	Cum. perc.
1=A	79	3.76	3.76	25	3.81	3.81
2=B	188	8.94	12.70	49	7.46	11.27
3=C	144	6.85	19.54	51	7.76	19.03
4=D	105	4.99	24.54	28	4.26	23.29
5=E	55	2.62	27.15	16	2.44	25.73
6=F	74	3.52	30.67	24	3.65	29.38
7=G	125	5.94	36.61	29	4.41	33.79
8=H	114	5.42	42.04	44	6.70	40.49
9=I	23	1.09	43.13	3	0.46	40.95
10=J	41	1.95	45.08	16	2.44	43.39
11=K	100	4.76	49.83	28	4.26	47.65
12=L	103	4.90	54.73	34	5.18	52.83
13=M	153	7.28	62.01	52	7.91	60.74
14=N	46	2.19	64.19	18	2.74	63.48
15=O	36	1.71	65.91	9	1.37	64.85
16=P	92	4.37	70.28	37	5.63	70.48
17=Q	4	0.19	70.47	2	0.30	70.78
18=R	100	4.76	75.23	29	4.41	75.19
19=S	238	11.32	86.54	63	9.59	84.78
20=T	68	3.23	89.78	21	3.20	87.98
21=U	9	0.43	90.20	0	0.00	87.98
22=V	54	2.57	92.77	20	3.04	91.02
23=W	102	4.85	97.62	32	4.87	95.89
24=X	3	0.14	97.77	3	0.46	96.35
25=Y	14	0.67	98.43	11	1.67	98.02
26=Z	33	1.57	100	13	1.98	100
Total	2103	100		657	100	

Table A shows the distributions of author names (as characterized by their first letter) separately for articles with one author (second column) and more than one author (first column).

The distributions are identical according to a Kolmogorov-Smirnov test of equal distributions: The test outcome is a corrected p-value of 0.990. Furthermore, according to Wilcoxon matched-pairs signed-ranks test, the distributions are equal (p-value = 0.81). Hence, authors whose names occur later in the alphabet are not less inclined to collaborate in joint authorships. This supports the assumption that the size of the authorship group is independent of an individual's position in the alphabet.[25]

D. Definitions of the independent variables in the name ordering strategy equations

The empirical proxies used for evaluating the inequality in academic standing across the author group are the (natural) logarithm of the standard deviation of scientific weight and the logarithm of the standard deviation of scientific age. The log-transformation is chosen because of the expected decreasing marginal effect of more (years of) publications on the variable to be explained. Actually, every time the log of a standard deviation is taken, we calculate the log of the standard deviation plus one. Another inequality proxy included in the specification is a dummy variable that indicates whether at least one of the co-authors has a non-academic affiliation (whereas at least one of the remaining co-authors doesn't).

The average (log) scientific weight and age of the author group is used as proxies for their average scientific standing. The distribution of co-author names per author-group over the alphabet is characterized by means of the average and the standard deviation of the *letter* rank. The academic importance of articles is measured by the impact factor of the journal and the number of pages of the article."One-shot author groups", i.e. groups that have not previously collaborated (insofar as this has led to a publication), are distinguished from longer-term co-operations.[26] Finally, a dummy variable is included that is one whenever at least one of the co-authors is female and zero otherwise, and one that is 1 for groups of US-authors exclusively.

Table 1 Frequency distribution of number of authors and name ordering over articles

# authors	# articles	%	# authors	# alphabetic	*P(AB)* (%)	Pα (%)
1	1033	45	1033			
2	946	41	1892	858	91	81
3	282	12	846	232	82	79
4	41	2	164	28	68	67
5	7	0	35	4	57	57
6	1	0	6			
8	1	0	8			
>1	1278		2921	1122	88	80
Total	2311	100	Different authors: 2103			

Table 2 Determinants of scientific weight

Variable	I OLS Sc. Weight	II OLS Sc. Prod	III Med Reg Sc. Weight	IV Med Reg Sc. Prod	V OLS LOG(Weight)	VI OLS LOG(Prod)
PANEL A: TOTAL SAMPLE						
Letter	-.001 (.01)	.0003 (.001)	.006 (.005)	.0004 (.0006)		
Log(letter)					.01 (.02)	.01 (.02)
Scientific age	1.56*** (.04)		1.35*** (.02)			
Log(sc. age)					1.46*** (.02)	
US base	1.00 (.71)	.05 (.04)	.60* (.32)	.062* (.037)	.02 (.03)	.06** (.03)
Asia base	-1.30 (1.83)	-.19* (.10)	-1.07 (.84)	-.22** (.10)	-.12 (.08)	-.21** (.08)
Female	-3.70*** (1.09)	-.42*** (.06)	-1.75*** (.50)	-.37*** (.06)	-.24*** (.05)	-.43*** (.05)
Non academic 1st affiliation	-2.75*** (1.05)	-.23*** (.06)	-1.55*** (.48)	-.28*** (.06)	-.20*** (.04)	-.29*** (.05)
N	2058	2058	2058	2058	2058	2058
(Adj) R-sq	0.45	0.04	0.34	0.03	0.66	0.05
PANEL B: ESTABLISHED HALF						
Letter	-.017 (.02)	-.0006 (.001)	**-.035**** **(.0179)**	**-.0017*** **(.0010)**		
Log(letter)					**-.033**** **(.015)**	**-.034**** **(.016)**
Scientific age	1.31*** (.09)		1.02*** (.07)			
Log(sc. age)					.64*** (.04)	
US base	.47 (.71)	-.07 (.06)	1.72 (1.08)	.061 (.067)	.04 (.03)	.005 (.03)
Asia base	-2.92 (1.83)	-.10 (.19)	-1.04 (3.24)	-.05 (.20)	-.06 (.09)	-.05 (.09)
Female	-5.88* (3.14)	-.24 (.15)	-2.77 (2.50)	-.15 (.15)	-.16** (.06)	-.11 (.07)
Non academic 1st affiliation	-1.84 (2.34)	-.02 (.11)	-2.14 (2.51)	-.04 (.12)	-.052 (.05)	-.02 (.05)
N	952	952	952	952	952	952
(Adj) R-sq	0.19	0.01	0.11	0.01	0.22	0.01

*10% significant; **5% significant; ***1% significant. Absolute standard errors are between brackets.

Table 3 Test if lower name-ranked authors see a faster growth in publications

Variable	Equation I Sc. Prod	Equation II Log(Prod)
Letter (demeaned)	.0005 (.0007)	
Log(letter) (demeaned)		.0172 (.0151)
Scientific age (demeaned)	.0139*** (.0023)	
Log(sc. age) (demeaned)		.2483*** (.02567)
Letter*Scientific age (both demeaned)	**-.00013*** **(.00008)**	
Log(letter)*log(sc. age) (both demeaned)		**-.0476*** **(.0282)**
US base	.0308 (.0396)	.06** (.03)
Asia base	-.1055 (.1066)	-.21** (.08)
Female	-.3165*** (.0637)	-.43*** (.05)
Non academic 1st affiliation	-.1621*** (.0607)	-.29*** (.05)
Constant	1.340*** (.0310)	
N	2058	2058
(Adj) R-sq	0.04	0.09

*10% significant; **5% significant; ***1% significant. Absolute standard errors are between brackets.

Table 4 Determinants of name ordering strategies of author groups

Variable	Equation I -Base- Total sample	Equation II -No age- Total sample	Equation III -No weight- Total sample	Equation IV -Base- 2 authors	Equation V -Base- 3 authors
Log average scientific age	-.0337 (.0303)		-.1024*** (.0229)	-.0458 (.0288)	.0470 (.1046)
Log st dev of scientific age	.0146 (.0160)		.0488*** (.0134)	.0081 (.0137)	.0530 (.0694)
Log average scientific weight	-.0923*** (.0253)	-.1102*** (.0181)		-.0534** (.0241)	-.3273*** (.0776)
Log st dev of scientific weight	.0707*** (.0196)	.0806*** (.0154)		.0491*** (.0165)	.2246*** (.0656)
Average letter	.0009** (.0004)	.0009** (.0004)	.0009** (.0004)	.0006* (.0004)	.0010 (.0013)
Sd of letter	-.0010** (.0005)	-.0010** (.0005)	-.0010* (.0005)	-.0010** (.0005)	-.0012 (.0018)
Difference in group in (non-academic) affiliation (d)	-.0173 (.0201)	-.0174 (.0201)	-.0124 (.0224)	-.0117 (.0217)	-.0293 (.0522)
Entire group from US (d)	.0054 (.0165)	.0046 (.0166)	.0103 (.0179)	-.0024 (.0169)	.0393 (.0473)
Impact score of journal	.0072 (.0099)	.0076 (.0100)	.0059 (.0106)	.0082 (.0101)	-.0077 (.0286)
Number of pages of article	-.0027*** (.0008)	-.0027*** (.0008)	-.0030*** (.0009)	-.0028*** (.0009)	-.0032* (.0018)
One of the authors is female (d)	.0107 (.0199)	.0126 (.0199)	.0200 (.0221)	-.0040 (.0194)	.0182 (.0544)
One shot author group (d)	.0262 (.0172)	.0262 (.0172)	.0473*** (.0178)	.0221 (.0187)	.0462 (.0432)
Number of authors	.0468*** (.0139)	.0478*** (.0139)	.0562*** (.0149)		
N	1233	1233	1233	923	276
Pseudo R-sq Loglikelihood	0.123 -391.7	0.121 -392.6	0.097 -403.2	0.100 -253.2	0.169 -112.2

*10% significant; **5% significant; ***1% significant. Absolute standard errors are between brackets. ([a]) dF/dx is for a 1 (percent) point change of the independent continuous variables measured at the average value ([d]) dF/dx is for a discrete change of dummy variable from 0 to 1.

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[2] The occurrence of multi-authored papers has increased rapidly over the last few decades. For instance, in two leading economics journals, i.e., *Journal of Political Economy* and *American Economic Review*, it has increased from six (JPE) and eight (AER) percent in 1950 to 40% and 55% in 1993 (Hudson, 1996). Sutter and Kocher (2004) document this trend in a broader range of (high quality and lower quality) economics journals.

[3] The percentage varies over academic disciplines and is highest in economics (see Engers et al., 1999; Laband and Tollison, 2000). In the psychological literature, for instance, the percentage of alphabetically ordered articles is only forty percent.

[4] There are many seemingly irrelevant individual characteristics that may co-determine one's success in life, for instance, beauty and height (Hamermesh and Biddle, 1994) and first names (Bertrand and Mullainathan, 2004). The alphabetic rank of last names might be another seemingly irrelevant factor correlated with success.

[5] Our analysis is restricted to a database gathered from the economics literature, since the dramatic difference between the neighboring disciplines of economics and psychology demonstrates that name ordering behavior is discipline-specific. Hence, our results cannot be generalized to other disciplines than economics (see also Laband, 2002).

[6] The differences in approaches to this first question and findings between Einav and Yariv (2006) and our study will be discussed in detail in subsequent sections of the paper.

[7] This overall p_α is calculated as the weighted average of the p_α's over all n. The observed alphabetic percentage is higher the fewer authors are involved: it is 91% for two authors and 57% for five authors. Moreover p_α decreases as n increases: Two authors use an alphabetic strategy in 81% of cases, whereas this percentage decreases to 79% for three, to 67% for four, and to 57% for five authors.

[8] Einav and Yariv (2006) proxy productivity by tenure at highly ranked schools in the US, fellowships of the Econometric Society and Nobel Prize and Clark Medal winnings.

[9] We do not correct for the origin of the name of an author. For instance, if Chinese authors have names that rank high (or low), on average, and if Chinese are more (or less) productive, this would entail a

problem. However, the analysis by Einav and Yariv (2006), who did control for the origin of names, showed that this was not the case.

[10] Truncating the sample based on the dependent variable is econometrically admissible because we wish to predict the effect of alphabetic name position on one's scientific weight for a *population* of economists with a higher than median number of publications. This practice can be compared to estimating wage equations for a sample of wage earners (excluding people without jobs). This type of selectivity is not worrisome as long as the equation has been estimated based on a representative sample of the total population one wishes to make predictions for.

[11] We are grateful to one of the anonymous referees who suggested this additional analysis.

[12] We also ran these regressions for the sub-sample of below median producers. These showed that someone's alphabetic position is a non-significant determinant of total production and of productivity at the earlier stage of one's career. This supports the assumption we made in the beginning that merit and alphabetic rank are uncorrelated. This set of regressions showed furthermore that the significant control variables in the entire sample are even more significant in the below median sample, indicating that they determine production and productivity primarily at earlier career stages.

[13] Einav and Yariv (2006) find no significant results for the other performance measures analyzed, namely fellowships of the Econometric Society and Clark Medal and Nobel Prize winners.

[14] The results from estimating equations II and III on the sub-samples of 2 and 3-authored articles are virtually the same as the results in columns IV and V.

[15] We checked whether the effects of an author group's standard deviations in scientific weight and age on name-ordering are purely caused by, what we call a "PhD student-supervisor effect": i.e., the habit of some supervisors to always position themselves first (or last) when collaborating with their PhD-students. To this end, we dropped all observations from the sample that included one author with the lowest possible scientific weight and/or the lowest possible scientific weight (n=120) and reran the regressions. The estimation results on the sample excluding these novices were similar to the results in Table 4. We conclude that the relationship between an author group's differences in scientific standing and the probability of using a merit strategy is caused by a more widely applied mechanism than only within the group of PhD-students with their supervisor.

[16] The averages and standard deviations of scientific weight and age are obviously correlated to each other. This statistical phenomenon could possibly cause the opposing effects on the probability of

following a merit strategy of the standard deviations (both positive) and the averages (both negative). We reran the regressions twice to check whether this was the sole cause of our finding: once without averages and once without standard deviations. All results kept standing when only inserting averages or standard deviations of the weight and age variables.

[17] The number of pages in a journal has not been standardized according to differences in number of words per page across journals.

[18] The impact factor is based on the objective ranking, the Social Science Citation Index (SSCI), annually published by the Institute for Scientific Information (ISI). The impact factor for each journal is calculated by using the following formula: impact factor year X = (Cites in year X to articles published in year X-1 and in year X-2)/(Number of articles published in year X-1 and in year X-2). We use X=1999.

[19] Preferably, an author's 'birth year' would be defined by the year in which an author completed her PhD, but this was very difficult to obtain.

[20] The *Web of Science* database -used for the articles related variables- was unsuitable because it includes publications as of 1988 only.

[21] For 196 authors whose first names were not clearly identifiable as male or female (we had for instance difficulties with many of the Chinese and Japanese names or with Western names that are used for both males and females) we consulted their personal websites. These often give a clue about gender. We gathered the email addresses of authors without identifiable personal website and sent them a mail with our information request. In the end, the number of authors with unknown gender was 45. We dropped them from the sample for analysis. In an alternative specification, not reported in this paper, we labeled their gender as male and used an extra dummy indicating 'gender unknown'. This alternative specification rendered the same results.

[22] If an author has changed affiliations over time, we counted the most recent affiliation, unless the author has worked in a different institution for the majority of the time period in which most of his/her publications have been produced. Whenever an author works for both types of institutions, we consider the institution that has been mentioned first (in the author affiliations footnote in the article) as his/her main affiliation.

[23] If an author has worked in several institutions over the relevant period and if these institutions are located in different geographical areas according to our definition, we have assigned both values to the geographical location variable.

[24] Of course, some authors might not have published in 1969, but did so in, for instance, 1968 and 1970. Their scientific ages will be truncated as well. However, since the economists in our database publish more than one article per year on average in any of the journals included in the SSCI, this will not increase the proportion of truncated values by much.

[25] Einav and Yariv (2006) also find that the relationship between alphabetic name rank and the size of the author group is insignificant. They only find a small effect for the small fraction of articles with more than three authors.

[26] We acknowledge that we cannot distinguish between ‘one-shot games’ and ‘first periods’ of longer-term co-operations.