DOES AUTHOR ORDER MATTER?

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December 20, 2020

ABSTRACT

There are two common norms of ordering author names in a scientific publication: Alphabetical order and contribution-based. Could the alphabetic order norm make the alphabetic rank of a author's last name an irrelevant factor co-determining academic success? Previous work found such bias for authors in Economics - but does it hold in other disciplines? In the "Theory of Computer Science" (TCS) field, there is a strong alphabetic order norm: more than 97% of the papers in its two crown conferences, STOC and FOCS, between 2000 and 2009 follow it. Based on data collected from the DBLP and the Semantic Scholar, I test whether the last name's alphabetic rank is correlated with academic success in TCS while controlling for "scientific age" and ethnicity. I find no such main effect, and I conclude that no evidence that the last name's alphabetic rank is a factor in the academic success in the TCS community. Nevertheless, I identify possible limitations of my analysis and propose future directions to address them.[1]

1 Introduction

The choice of author order in scientific publications is an issue that attracts attention in various journals and scientific associations [1] [2]. Different scientific fields vary in the name order norms. In some disciplines, the order conveys important information about each author's contribution, such in Psychology, and in this case, earlier appearance means mostly a greater contribution. Meanwhile, in other fields, such as Economics, the norms are different such as alphabetical order of author's names. In this case, the position should signal nothing, assuming that talent and willingness to work hard is independent of the name lexicographical position with additional controls such as Ethnicity. Indeed, Maciejovsky et al. found that in Economics, the author order of more than 87.49% of the publication in leading journals is alphabetical, compared to around 33.04% in Psychology. In comparison, the expected proportions are 42.62% and 32.72%, respectively [3]. Generally speaking, the prevalence of alphabetic order varies greatly between different scientific fields; nevertheless,most of the scientific publication follow contribution-based norm [4] [5].

But what if, under the alphabetic norm, people consider the name order as a meaningful sign? This is an important question as it might impact authors career: hiring, promotions, tenure decisions, receiving additional funding, or attracting brighter students. If there is any evidence that in a scientific community that follows the alphabetic norm, there is a link between academic success and the lexical position of the last name or the occurrence of being first-author in multi-author papers — then this community should probably consider its order norms to avoid such bias.

1.1 Related Work

A recent literature review based on seven studies has concluded that the accumulative evidence is that researchers with a surname that appears lexically later suffer disadvantage in fields with alphabetic order norm [5]. Overall, only very few disciplines were examined in this line of research, most notably Economics. Shah and Wang (2018) propose at least two type of bias effects that could potentially manifested such bias [6]. First, an implicit bias stemming from the

[1]The codebase for this work is available at https://github.com/shlomihod/does-author-order-matter

human cognitive bias of primacy - "first is the best" [7]. Second, an explicit bias arises from how papers are referred. For example, it is accepted practice to cite papers as *"First Author et al."* or to order a bibliography alphabetically.

A common assumption is that the effect of a surname surfaces only after a few years since the first publication of an author, because reputation might take time to be built up. Indeed, some studies' findings are aligned with this premise. Einav & Yariv (2006) documented multiple correlations between surname initial positions and professional success in academia [8]. They observed a statistically significant disparity in surname distribution between tenured and untenured faculty in top-5 and top-10 Economics departments in the US; the former's last name is closer to the start of the alphabet than the latter. However, these findings gradually disappeared for top-20 and top-35 departments. The analysis was conducted while controlling for potential confounding factors (e.g., nationality, race and religion, years since receiving a Ph.D.). The same pattern holds for another proxy of academic success, fellowship in the Econometric Society. For the Nobel prize and Clark medal laureate, this bias shows up in the same direction, but it is not statically significant, probably due to the small sample size. To contextualize their finding, Einav & Yariv applied the same analysis in Psychology, a close field to Economics in which the contribution norm is predominantly used. The results for Economics researchers do not reproduce for Psychology researchers.

Other measures of success were also explored. Van Praag and van Praag (2008) found a significant effect of surname initial alphabetic position on both the number of publications and average and the number of publications per year, only for authors with an above-median number of publications [9]. The last constrain resembles the application of Einav & Yariv's result only for top departments. The authors' data was generated by collecting all the authors of 11 Economics journals. The analysis was performed using ordinal and robust regression, with controls for geographical location, gender, affiliation, and "scientific age" (year passed since the first publication).

Hilmer & Hilmer established a link between authorship and salary of agricultural economics faculty members of top-20 PhD-graduate programs in the US [10]. Interestingly, the estimated return of a paper with the author's alphabetical order is significant, while it is not a non-alphabetic paper. They found that this return is not associated with being the lead author of the trailing author.

The natural follow-up question is how individuals actually interpret and assign credit to a given author order. In a survey experiment, Maciejovsky et al. (2009) presented to academics from Economics (mostly alphabetic-ordering norm), Psychology (mostly contribution norm) and Marketing (no strong norm), pairs of author groups, in which the name are sampled randomly from common British name. The name order in each group was sometimes alphabetically and sometimes not. The participants were asked to compare the contribution of a given "target" author from each pair. As expected, participants from Psychology and Marketing assigned a greater contribution to the first author, but surprisingly, academics from Economics did so as well.

There are two additional lines of research that are related to the question of whether the last name lexical position is related to academic success. The first examines whether the authors respond strategically to the alphabetic norm. There is evidence that the answer is positive, based on different kinds of analysis, such as the number of coauthors in publication, whether the alphabetic norm is followed, and a surname manipulation [5] [8] [11] [9]. The second explores gender bias in author order [12] [13].

1.2 My contribution

In this work I focus on the sub-field of Theory of Computer Science (TCS), where the author order of the ' majority, more than 97%, of multi-authored papers in its two primary conferences, STOC and FOCS, is alphabetical (see section 2). This proportion is higher than any other field studied in-depth, to the best of my knowledge.

My primary research question is whether the alphabetic order norm could make the alphabetic rank of the last name an irrelevant factor co-determining academic success. Of course, without performing proper experimental design, it would not be possible to address this question. Therefore, I aim only to evaluate whether there is a correlation between alphabetic position and academic success in a field where the alphabetic order norm is dominant, namely TCS. The community's scholars are defined by being an author in at least one publication in the community's two leading venues, STOC and FOCS, between 2000 and 2009.

The explained variable, academic success, is measured using an AI-based method, number of influential citations, by Semantic Scholar. It is an author-level measure of productivity and citation impact based [14]. I do not use the more common measure of h-index because of the difficulty of collecting reliable data (see the next section) [15]. The predictor variable is either the alphabetic last name rank (e.g., $A = 0, B = 1, C = 2 \ldots$) or the proportion of papers in which a scholar is the first author. The second score is a contribution of this work; it is 'emprical" measure of the actual appearance of an author at the first position, and it is distinct from appearing early in the "theoretical" lexical order of the alphabet. There are possible confounder, such as different distribution of last names of authors along the year or between origin, I include in the analysis control variables such as scientific age and ethnicity (inferred on the last name).

I find no significant effect of the predictor variables on the explained variable given the controls. It suggests that the last name's alphabetic rank is not a factor in the academic success in the TCS community. Originally, I planned to carry out this analysis also for the Machine Learning community, where the contribution norm is more common, to serve as a baseline. However, I could not collect reliable data on the authors' academic success measures in this community. Nevertheless, I report the available descriptive statistics for papers and authors from the Machine Learning community.

The remainder of this paper is structured as follows. Section 2 presents the methodology, particularly what data was used and which statistical analysis was performed. Then, the findings are presented in section 3. Finally, I discuss the results, propose future direction and conclude this work in section 4.

2 Method

2.1 Data

The level of analysis in this work is author-wise. First, we need to identify which authors are part of the TCS community, and then collect various variables: a measure of academic success, representation of surname position in the alphabet, proportion as the first author, and control variables of ethnicity and scientific age.

I define a community of research through its conferences. The IEEE Annual Symposium on Foundations of Computer Science (FOCS) and the Annual ACM Symposium on Theory of Computing (STOC) are considered the two top conferences in the theory of Computer Science [16]. The subjects in this research are the individuals who published at least one paper in these two conferences between the years 2000 and 2009.

I experimented with multiple datasets and platforms such as DBLP[2], AMiner[3], Semantic Scholar[4], Google Scholar[5], Open Academic Graph[6] and Microsoft Academic Graph[7]. Establishing the data pipeline in this project was challenging because it required linking conferences to papers and authors to papers. For example, only the DBLP and Microsoft Academic Graph store the conference in an accessible and structured manner. Others hold this information as a free text, in which there are multiple string representations for a conference in a given year. On top of that, the same data source might have a reliable link between authors and papers, but not necessarily between papers and conferences. In Google Scholar, there is an author page (with academic success measure, such as h-index [15]) only for authors that actively opened a profile, and from exploratory data analysis, it seems biased (e.g., by ethnicity). To my current understanding, Microsoft Academic Graph provides all the requirements well. Still, I came to this conclusion relatively late in the projects, and it also took a while to get access to this data source after applying.

Therefore, I decided to use two data sources: (1) DBLP for linking conferences to papers, and (2) Semantic Scholar for linking papers to authors. The linking between papers from DBLP and the Semantic Scholar is done using the paper's digital object identifier (DOI). The Semantic Scholar API is limited in its search ability and requires a standardized identifier. Fortunately, for all of the FOCS and STOC papers, the DOI is present in DBLP.

2.1.1 Data Collection & Preprocessing

To recap, first, all papers of STOC and FOCS between 2000 and 2009 are exported. Using the DOI, all of the 1,517 papers are queried from the Semantic Scholar. The set of all authors is created, and each one of them is queried from the Semantic Scholar, which returns, among other, the (1) academic success score (number of influential citation) and (2) list of publication. The scientific age is calculated using the latter: the number of years passed since the first publication until 2021. The author name is standardized by stripping accents and diacritical marks and using the `nameparser`[8] to extract the last name adequately for various origins. Finally, the initial *letter* of the surname is extracted and assigned a natural number ascendingly, where $A = 0, B = 1, \dots, Z = 25$. There are 1,321 authors, and one additional author is not found by the Semantic Scholar API.

[2] `https://dblp.org/`
[3] `https://www.aminer.org/data`
[4] `https://www.semanticscholar.org/`
[5] `https://scholar.google.com/`
[6] `https://www.microsoft.com/en-us/research/project/open-academic-graph/`
[7] `https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/`
[8] `https://nameparser.readthedocs.io/en/latest/`

2.1.2 Ethnicity & Gender

The control variables are important as the distribution of last name initials might differ across the different groups. To accommodate that, I use the Python package `ethnicolr`[9] to infer the ethnicity (Asian/African/European) from a full name. It is based on a deep learning model that utilizes a dataset of over 140k name/race associations scrapped from Wikipedia [17]. `ethnicolr` reports in their GitHub repository that "SCAN Health Plan, a Medicare Advantage plan that serves over 200,000 members throughout California used the software, ... They only had racial data on about 47% of their members so used it to learn the race of the remaining 53%. On the data they had labels for, they found .9 AUC and 83% accuracy for the last name model."

Unfortunately, I could not find a reliable tool to infer gender from names. I explored several Python packages and online API, and it is not clear to me that there is such a service that handles well non-English names, as a recent study got into similar observation [18]. Therefore, I decided not to use this control variable. I argue that the ethnicity information is probably much more important than gender because the former affect the first and last name directly, while the latter has a greater impact on the first name (although I cannot rebut the effect on the last name).

2.1.3 Machine Learning community

For the sake of completeness, I report the data collected for the ML community. It is defined based on the Conference on Neural Information Processing Systems (NeurIPS) and the International Conference on Machine Learning (ICML). From DBLP, between the years 2000 and 2009, there are 3,414 papers and 4,181 authors. Unfortunately, most papers have no DOI, so it was impossible to query the Semantic Scholar to get the academic success score. It means that any analysis that does not involve the explained variable, academic success, can still be carried reliably also for the ML community.

2.2 Models

To assess whether there is a correlation relationship between the variables in interests, I performed multiple regression analysis, similarly to Van Praag and van Praag (2008) [9]. The regression formula is always

$$\boxed{\text{\#Influential citation} \sim \text{Order} + \text{Scientific age} + \text{Ethnicity.}}$$

where the "#Influential citation" and "Order" are the explained and predictor variables, respectively, and "Scientific age" and Ethnicity" serve as control variables.

In total, 24 models are fitted and analyzed using the Python package `statsmodels` [19], spanned by three dimensions:

1. There are three operationalization to the "Order" variable: (1) surname initial, (2) percentage of first-author papers, and (3) percentage of last-author papers.
2. Because we do not know a-priori what is the shape of a possible relationship between the variables, I use for type for regressions: (1) OLS, (2) OLS with logarithmic transformation, (3) Robust linear models (RLM), and (4) Quantile regression. The default hyperparameters are used.
3. Restricting the TCS authors according to the number of influential citation score: either the score is (1) at least 1 or (2) at least the median. The former is done to reduce the effect of potential outliners and the latter if the correlation surfaces only for the established authors. The second restriction goes along the same lines as previous work [8] [9] [5].

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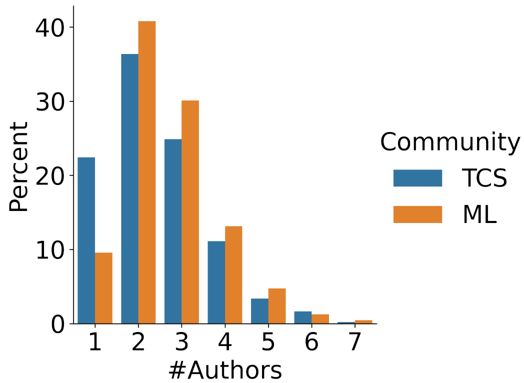
3 Findings

The data on papers and conferences is valid for both of the communities. Before we interpret the regression model results, let's understand better the communities and their relation to authorship characteristics.

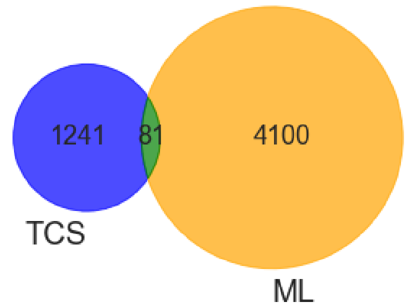
3.1 Author, coauthors, and alphabetic order

A basic question is how the number of authors distributes in each one of the communities. Figure 1a shows the distributions as histograms. Clearly, single author papers appear more than double the proportion in TCS than ML, yet

[9] `https://github.com/appeler/ethnicolr/`



(a) Histogram of number of authors per publication, calculated for each community separately. For the sake of a clear visualization, the bins of eight or more authors are discarded, and they account for not more than one percent pf publications within each one of the communities.



(b) Venn diagram of the set of authors that published in each community.

Figure 1: Communities and Authors

the mode and the median for both of the communities are 2 authors. Kolmogorov–Smirnov (KS) test suggests that there is no statistically significant difference in this distribution between FOCS and STOC within TCS and between NeurIPS and ICML within ML. A KS test between the communities is statistically significant ($D = 0.128, p < 0.0001$).

The two communities are distinct in another aspect: the proportion of multi-author publications that follows the alphabetic author order. More than 97% of the papers follow this ordering in TCS for the conferences, but only around 41% for in. This is an overestimation for the "true" proportion of publication that follows the alphabetic norm because it could be that a contribution-based order is lexical by chance (see [9] for a correction method). Nevertheless, the gap here between TCS and ML is substantial, and it is not surprising because the alphabetic order norm is dominant in TCS. At the same time, it is the contribution norm that is more common in the ML community. What is notable is that this proportion in TCS is much higher than any other field studied in depth before.

So far, we have observed that the TCS and ML communities have different characteristics regarding the author groups in papers; but are the author themselves, as individuals are mutually exclusive sets? Figure 1b presents a Venn diagram of the authors published solely in the TCS conferences (FOCS, STOC) or the ML conferences (NeurIPS, ICML), and those published in both of them. Clearly, the intersection is rather small, and the vast majority of authors published within a single community. I note two additional anecdotally observations from the exploratory data analysis: (1) The intersection between the two conferences within a community is one order of magnitude greater than between the communities; and (2) the magnitude of the intersection between communities gets bigger in the next decade of 2010-2019.

The evidence so far suggests that the two communities exhibit different behavior regarding authors' numbers and order. That makes the 88 authors in the intersection interesting case-study. Could we identify whether they are "more part of TCS" of "more part of ML"? If so, which ordering norm do they follow when they publish a paper in a "other" community conference? For each author, I compute the ratio between the number of publications in ML and TCS. If an author has more than $\times 1.5$ publications in one community than the other, I define it as the author's "major" community. Naturally, if an author published only under a single community, it would be the same as their "major" community. For 66 authors out of the 88 published in both communities, I can identify a "major" community, but not to the rest 22 individuals. Now we can compute *for each author* what the percentage of their papers in each community that follows alphabetic order is. Then, we aggregate these proportions over the "major" community (of an author), shown in figure 2. Interestingly, for papers that are published in an ML conference with at least one TCS-"major" author (47 papers), the proportion of such papers that follows alphabetic author ordering is much higher, almost 66%, compared to papers written by at least one ML-"major author, almost 41%. The parallel analysis for TCS conferences reveals a much smaller drop of 2%. In this case, conducting hypothesis testing is not straightforward because a paper might be counted under the two "major" communities, depending on its authors' mix. These findings might suggest that "TCS" major author import their order norms into other publications, while these norms are much enforced in TCS conferences.

Finally, Figure 3 presents the correlation in the author level between the predictor, explained, and control variables, in addition to the number of publication, for the *TCS community only*. Recall that I managed to obtain reliable data for the

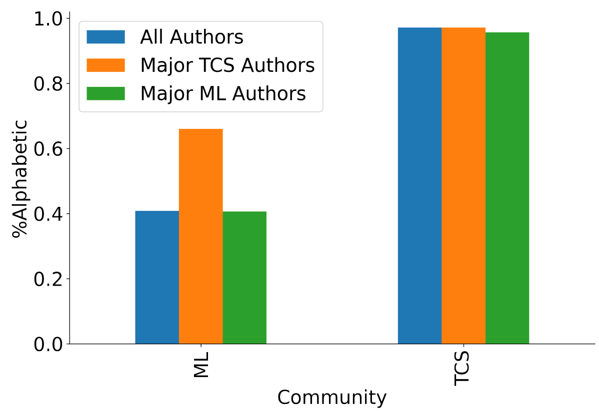


Figure 2: Proportion of papers with alphabetic author order grouped by community and existence of at least on author within a "major" community..

explained variable only for this community. The pattern of correlations shows two groups of variables. First, because of the strong alphabetic order norm in TCS, as expected, the letter is correlated with the proportion of being a first-author and anti-correlated with the proportion of being a last-author. Second, the variables related to publication - number of influential citations, number of publications, and scientific age - as expected, are correlated to each other. No strong correlation is observed between these two groups of variables. Nevertheless, only in the next sub-section, we perform the regression in a way that allows us to learn about the relationship between the predictor and the explained variables.

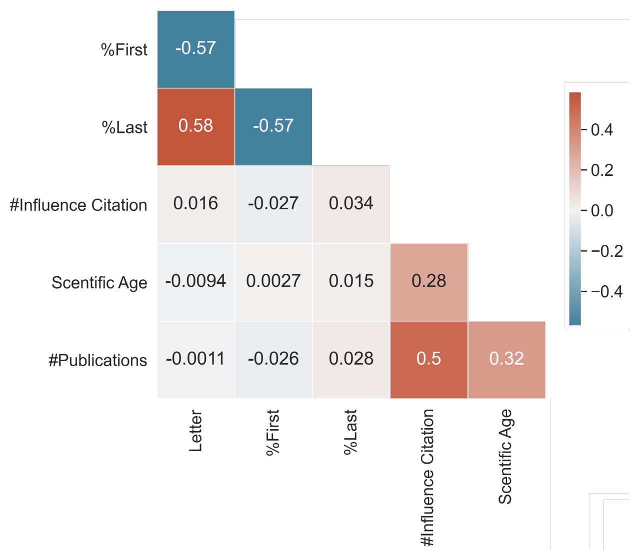


Figure 3: Correlation (Pearson's r) heatmap between the explained, predictor and the control variables for the TCS authors only.

3.2 Regression model results

The main effect of the "Order" variable, either as surname initial or percentage of publication with the first authorship, is examined overall the 24 fitted regression models. 5 of the respective coefficient are statistically significant with $p < 0.05$. To take into account the multiple comparisons and adjust the p-value correctly, I use the Benjamini–Hochberg procedure at level 0.05 to control the FDR (False Discovery Rate) [20]. Then, *there is no statically significant effect of any of the two order variables on academic success for the TCS community*. That holds for all the authors with at least one influential citation and score and the top half. We note that, unsurprisingly, the scientific age has an significant effect in all of the models, as well as controlling of FDR. Table 1 presents the results of 8 out of 24 regression models. The results of the rest of the models are similar.

	OLS	QR	OLS	QR
Letter	2.07 (3.15)	1.02 (0.98)		
First Proportion			-48.19 (49.05)	-23.00 (15.94)
Scientific age	18.03*** (1.79)	12.80*** (0.56)	18.07*** (1.78)	13.00*** (0.58)
Ethnicity (African)	-1.37 (108.26)	14.97 (22.59)	-13.99 (103.68)	14.68 (33.69)
Ethnicity (European)	-3.02 (52.33)	-1.40 (16.24)	-14.60 (50.78)	2.96 (16.50)
N	1221	1121	1170	1170
Adj./Pseudo R^2	.075	.076	.080	.082

(a) Sample: Authors with at least one influential citation.

	OLS	QR	OLS	QR
Letter	3.82 (5.91)	0.23 (2.40)		
First Proportion			-13.48 (97.38)	-20.38 (42.05)
Scientific age	15.32*** (3.46)	10.18*** (1.40)	14.84*** (3.35)	11.39*** (1.45)
Ethnicity (African)	-76.19 (205.66)	97.74 (83.57)	-95.32 (194.68)	81.31 (84.08)
Ethnicity (European)	-7.81 (100.47)	-41.79 (40.83)	-32.96 (95.76)	-46.75 (41.35)
N	591	591	571	571
Adj./Pseudo R^2	.027	.076	.028	.039

(b) Sample: Established half, top-50% of authors in number of influential citations.

Table 1: Results of 8 regression models out of 24. Each panel represents a different sample of authors. The predictor variable is either the initial letter of a surname or the proportion of being a first author. Each column holds the results for one model. OLS stands for Ordinary Least Squares and QR - Quantile Regression. For OLS, the adjusted R^2 is reported, and for QR - the pseudo R^2. The values in the cells are the regression standardized coefficients, and those in the parenthesis are the standard error.
*** $p < 0.001$

4 Discussion

In this work, I examine the dataset of conferences, papers, authors to assess whether there is an effect of last name position in the alphabet on academic success to Theory of Computer Science researchers. Through the analysis, the TCS and ML communities' characterizes concerning author order were compared, and the findings are aligned with the order norms in each community. Overall, I did not find any evidence for a relationship between last name and academic success in TCS. This conclusion seems surprising in light of the well-documented bias in Economics. The divergence might arise from (1) the fact that indeed there is no such bias in TCS; (2) insufficient amount of TCS authors, so the statistical hypothesis testing in the regression models did not have enough power; or (3) the fact that in TCS almost all of the publications follow the alphabetic order compared to Economics (87.49% [3]), so no matter what, the order of authors in TCS almost always does not carry any signal of contribution.

4.1 Future work

This work can be extended in multiple verticals. The most important direction that I identify is to use higher quality data. To the best of my knowledge, the Microsoft Academic Graph dataset is the best available source. In particular, it holds conferences in a structured way, and it allows to compute h-index relatively easily overall its stored authors. It will then be possible to define the TCS community using more conferences (e.g., from Cryptography) and extend the range of years.

By applying the same analysis to multiple disciplines, within and outside Computer Science, hopefully, one could test the conjecture stated above between the proportion of alphabetic order papers in a community and the existence of last name bias.

Finally, a very close line of research to this work is whether authors behave strategically to maximize their utility under the alphabetic, and which action they take, such as changing their name and picking coauthors with specific surname distributions. This is specifically interesting regarding authors that publish in multiple communities. Hopefully, a better understanding of these aspects could help design and better, fairer, and social-welfare maximizing publication norms.

References

[1] American Mathematical Society. The culture of research and scholarship in mathematics: Joint research and its publication. 2004.

[2] Henry Sauermann and Carolin Haeussler. Authorship and contribution disclosures. *Science Advances*, 3(11):e1700404, 2017.

[3] Boris Maciejovsky, David V Budescu, and Dan Ariely. Research note—the researcher as a consumer of scientific publications: How do name-ordering conventions affect inferences about contribution credits? *Marketing Science*, 28(3):589–598, 2009.

[4] Ludo Waltman. An empirical analysis of the use of alphabetical authorship in scientific publishing. *Journal of Informetrics*, 6(4):700–711, 2012.

[5] Matthias Weber. The effects of listing authors in alphabetical order: A review of the empirical evidence. *Research Evaluation*, 27(3):238–245, 2018.

[6] Nihar B. Shah and Jingyan Wang. There's lots in a name (whereas there shouldn't be), Nov 2019.

[7] Dana R Carney and Mahzarin R Banaji. First is best. *PloS one*, 7(6):e35088, 2012.

[8] Liran Einav and Leeat Yariv. What's in a surname? the effects of surname initials on academic success. *Journal of Economic Perspectives*, 20(1):175–187, 2006.

[9] C Mirjam Van Praag and Bernard MS Van Praag. The benefits of being economics professor a (rather than z). *Economica*, 75(300):782–796, 2008.

[10] Christiana E Hilmer and Michael J Hilmer. How do journal quality, co-authorship, and author order affect agricultural economists' salaries? *American Journal of Agricultural Economics*, 87(2):509–523, 2005.

[11] Georgios Efthyvoulou. Alphabet economics: The link between names and reputation. *The Journal of Socio-Economics*, 37(3):1266–1285, 2008.

[12] Nichole A Broderick and Arturo Casadevall. Meta-research: Gender inequalities among authors who contributed equally. *Elife*, 8:e36399, 2019.

[13] Heather Sarsons, Klarita Gërxhani, Ernesto Reuben, and Arthur Schram. Gender differences in recognition for group work. 2015.

[14] Oren Etzioni. Ai zooms in on highly influential citations. *Nature*, 547(7661):32–32, 2017.

[15] Jorge E Hirsch. An index to quantify an individual's scientific research output. *Proceedings of the National academy of Sciences*, 102(46):16569–16572, 2005.

[16] Faith Fich. Infrastructure issues related to theory of computing research. *ACM Computing Surveys (CSUR)*, 28(4es):217–es, 1996.

[17] Anurag Ambekar, Charles Ward, Jahangir Mohammed, Swapna Male, and Steven Skiena. Name-ethnicity classification from open sources. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge Discovery and Data Mining*, pages 49–58. ACM, 2009.

[18] Junming Huang, Alexander J Gates, Roberta Sinatra, and Albert-László Barabási. Historical comparison of gender inequality in scientific careers across countries and disciplines. *Proceedings of the National Academy of Sciences*, 117(9):4609–4616, 2020.

[19] Skipper Seabold and Josef Perktold. statsmodels: Econometric and statistical modeling with python. In *9th Python in Science Conference*, 2010.

[20] Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1):289–300, 1995.