Alphabetic Norm and Research Output

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Abstract

The norm in the economics profession is to order authors alphabetically in publications. Our examination of the articles published in 42 leading economics journals during the last 21 years finds that papers that do not follow this norm are shorter (by 3.7 percent), published in less prestigious journals (by 5.0 percent), and receive fewer citations (by 9.6 percent). This association survives various identification checks such as controlling for last-name initial combinations, teamwork history, and team fixed effects. Our findings shed light on how teamwork incentives interplay with social norms — in this case, a deviance from the alphabetic-ordering norm punishes alphabetically early members more than it rewards alphabetically late members.

JEL codes: D8, O3

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1. Introduction

How should the collaborators of a research project be ordered in their final publication? This is a sensitive question for many academic researchers. A failure to reach consensus on the author order could produce severe conflicts among collaborators. Contributions made by individual researchers in a research team are usually difficult to disarticulate, not to mention comparing the respective contributions and ranking them. For better or worse, there is a simple and easily justifiable solution used routinely in economics: order authors alphabetically by their last names.

This alphabetic norm is fair in the sense that last name is one of the most "exogenous" characteristics of a person. For adults who are old enough to start a research career, changing a last name is legally complicated and socially inconvenient. It is implausible that a researcher would take pains to do so in order to gain an earlier alphabetic position among coauthors. However, the apparent fairness of this norm involves an inherent lack of fairness, as alphabetically earlier last names have more visibility in

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publications. It has been extensively found that academics (including but not limited to economists) with alphabetically earlier last names are more successful (Tregenza, 1997; Merritt, 1999; Hilmer and Hilmer, 2005; Einav and Yariv, 2006; Efthyvoulou, 2008; Maciejovsky et al., 2009; Huang, 2015; Abramo and D'Angelo, 2017).[1] The alphabetic norm gives potentially unwarranted advantage to Professor(s) A. A truly fair solution would be to randomize the order across coauthors and preferably, signal the randomness to readers, as proved and practiced by Ray ⓡ Robson (2018).

In this paper, we take a step back from the fairness issue and ask a positive question — what if economists on a joint paper do not follow the alphabetic norm? To answer the question, we collect data on articles published in 42 leading economics journals over a 21-year period. Think of every coauthored article as the output of a research team. We use article length (number of pages) to measure the quantity of the team's output, and the article's journal ranking and citations to measure the quality of the team's output. We find that papers that deviate from the alphabetic norm are weaker by both quantity and quality measures. The quantity (length) margin shrinks by 3.7 percent, while the quality margin shrinks by 5.0 percent (measured by ranking) or 9.6 percent (measured by citations).

Since papers that do not follow the alphabetic norm may systematically differ from those following the norm, the identification issue is challenging in this study. We conduct three econometric experiments to ascertain whether the results are driven by confounding factors. First, authors with different alphabetic positions have different incentives in choosing coauthors. We examine the teams of coauthors with the same last-name initial combinations. For example, Ricardo and Smith have the initial combination RS, as do Robinson and Sanders. When Ricardo and Smith decide to work together, their concerns over the alphabetic norm should be no different from those of Robinson and Sanders. Within such initial-combination teams, some choose to follow the norm, while others choose not to do so. We rerun the previous study and reach the same findings.

Second, we pinpoint all coauthor teams in the sample and examine whether a deviance from the alphabetic norm still matters conditional on whether the team has ever deviated from the norm. Teams that always follow the norm are potentially different in how they view social norms and collaborative relationships compared to those who do not always follow the norm. Recall the earlier example. This time Robinson-Sanders and Ricardo-Smith are two distinct teams. The fact that Robinson-Sanders never perturb their order suggests that they are strict followers of the norm. Smith and Ricardo take a more flexible view of the norm, as some of their papers follow it while others do not. We find that conditional on whether they ever deviate, the papers that deviate from the norm remain weaker quantitatively and qualitatively.

Third, we combine the two previous experiments. With team fixed effects, we find that the papers not following the norm are shorter than those that do follow. The quality margin is now statistically insignificant, possibly because a given pair of coauthors target a stable tier of journals over time. However, once we keep only the pairs that choose more diverse journals, we find again that those papers

[1] This literature is thoroughly reviewed in Weber (2018). The alphabetic bias is also found in stock trading (Itzkowitz et al., 2016; Jacobs and Hillert, 2016), charitable solicitation (Meer and Rosen, 2011), and individual success (Cauley and Zax, 2017).

not following the norm are weaker in quality.

Our findings can be explained through the lens of Engers, Gans, Grant and King (1999), a theoretical model that insightfully analyzes the economic rationale behind the alphabetic norm. When the authors on a paper are alphabetically ordered, readers of the paper have two possible interpretations of the order. One is that the authors simply followed the norm, while the other is that the first author contributed more than the second. However, if the authors are not alphabetically ordered, only one interpretation applies. That is, deviating from the alphabetic norm implies that the first author contributed more than the second. Not following the norm would do more harm than good to the ex-ante incentives to contribute. If the alphabetically late person is made the second author, she would be only *partially* believed by future readers to have made less contributions, while the alphabetically early person, if made the second author, would be *fully* believed to have made less contributions. Therefore, a deviance from the norm causes more disincentives than incentives teamwide.

This paper sheds light on some deep underpinnings of social norms. Why do rational individuals follow established social norms? A simple answer is that a deviance from social norms would reveal unfavorable information about them. For example, an ambitious student should avoid using drugs even if drugs have no negative impact on her health. In this case, from the perspective of an ambitious student, it is rational to follow the social norm of avoiding drugs. Our study illustrates that the rationale behind the adherence to social norms is more nuanced than that. Norms such as alphabetic ordering come with an incentive structure behind it. Given an established norm, not following the norm cannot align the underlying teamwork incentives as well as when the norm is followed. In our study, papers that deviate from the norm turn out to be, with all else held equal, weaker in quantity and quality, indicating that there are better aligned incentives as a result of following the alphabetic norm. For this reason, we consider this study not as a navel-gazing of economists but rather as a demonstration of team incentives under the hood about which even non-economists should care.

Another contribution of this paper is to explain why most economists follow a norm that is neither merit-based nor effort-based. We argue that this is because breaking the norm would risk reducing team output and therefore hurting the whole team. Economists seem to favor merit- or effort-based rules as they (we) have ingrained trust in individual rationality (i.e. *homo economicus*). But modern economics also emphasizes growing the pie over dividing the pie. Both doctrines are reflected by an adherence to the alphabetic norm in the economics profession itself. Because of self-interest, a deviance from the alphabetic norm does more harm than good to the team output. So as a trade off, the seemingly *un*economic norm is followed in most cases.

The rest of the paper is organized as follows. In Section 2, a conceptual framework is provided to inform our hypothesis. We describe our data in Section 3 and report our results in Section 4. In Section 5, we conclude.

2. Conceptual Framework

In this section, we build a model to inform our later empirical investigation. Our model is in spirit a variant of Engers et al. (1999). Unlike their model that focuses on the strategic interactions between coauthors, our model concentrates instead on team output. The idea of our model is straightforward. Intellectual collaboration on a paper is essentially a team production of knowledge with complementary efforts made by coauthors. All else held equal, the team output is greater when the effort level of each author increases. Readers cannot observe the effort made by each author, so they use the observed author order to infer each author's contribution and give her credit accordingly. Owing to the existence of the alphabetic norm, an ambiguity in relative efforts encourages symmetrically more efforts, leading to a greater output level when the authors are alphabetically ordered.

Consider two authors A and B. They collaborate on knowledge production using the technology[2]

$$Y = \min\{x_A, x_B\}, \tag{1}$$

where x_k, $k = A$ or B, is the contribution level of author k. The contribution of each author k depends on her effort e_k and a random term μ_k that represents non-effort contributions such as inspirations:

$$x_k = e_k + \mu_k. \tag{2}$$

The two random terms μ_A and μ_B satisfy

(i) $\mu_A \geq 0$, $\mu_B \geq 0$,

(ii) $E(\mu_A) = E(\mu_B) = \bar{\mu}$,

(iii) $\Pr(\mu_A \geq \mu_B) = q$, where $0 < q < 1$.

Basically, author A's non-effort contribution has a probability $0 < q < 1$ to second-order stochastically dominate that of author B. That is, the two random terms have the same mean but either one could have a larger variance than the other.

The cost of making efforts equals $x_k^2/2$. Both authors are risk-neutral. For simplicity, we keep the two authors in collaboration in utility and ability, in order to isolate the mechanism through (dis) incentives. All settings up to this point are public information. The timing of events is as follows:

Date 1 The "nature" tells the two authors whether they should follow the alphabetic norm or not.[3] If they are told to follow it, author A is automatically the first author and author B the second. If they are told not to follow the norm, they will decide their order later on date 3 by comparing

[2] The strictly complementary contributions by assumption spare us the potentially complicated substitutability between the two coauthors. Think of this assumption as the scenario where the two authors' comparative advantages coincide with their absolute advantages, such as a "new theory plus new empirical evidence" paper written by a pure theorist and a pure empiricist.

[3] The "nature" here is a term that we borrowed from the game theory literature. It means a player who selects from among her strategies randomly, based on a predetermined probability distribution, rather than strategically, based on payoffs.

their relative contributions x_A and x_B. Readers never know what the nature reveals to the two authors, except that the probability for a given pair to follow the norm is $0 < p < 1$.

Date 2 Given the outcome on date 1, the two authors make efforts e_A and e_B, respectively.

Date 3 The random terms μ_A and μ_B are realized, such that x_A, x_B, and Y settle. If the two authors were told on date 1 by the nature not to follow the alphabetic norm, the one with a greater x_k becomes the first author and the other the second author. If they were told by the nature to follow the alphabetic norm on date 1, they enforce the norm now. In both cases, the order and Y are disclosed to readers. Readers give 2/3 (credit) of Y to the side they believe to have a greater contribution, and 1/3 (credit) of Y to the other.

To solve the model, let us start with date 3. Remember that readers can observe neither whether the authors adopted the norm nor their effort levels. They have to infer who made the greater contribution in order to give authors credit. From their perspective, the states of the world are as follows:

Case	Probability
Author A has a smaller contribution, and is the 1st author	$p(1-q)$
Author A has a greater contribution, and is the 1st author	$pq+(1-p)q=q$
Author B has a smaller contribution, and is the 1st author	0
Author B has a greater contribution, and is the 1st author	$(1-p)(1-q)$

That is, author A may be made the first author either by luck (i.e. dictated to follow the alphabetic norm) or by contribution, whereas author B can make the first author only by contribution.

Suppose that readers observe that author A (B) makes the first (second) author — denote this publicized alphabetic order by a plus sign (+) — and a corresponding output level Y^+. Y^+ will be divided by readers into R_A^+ and R_B^+, given to the two authors respectively:

$$R_A^+(e_A, e_B) = \left[\frac{p(1-q)}{p(1-q)+q} \times \frac{1}{3} + \frac{q}{p(1-q)+q} \times \frac{2}{3}\right] Y^+(e_A, e_B),$$
$$R_B^+(e_A, e_B) = \left[\frac{p(1-q)}{p(1-q)+q} \times \frac{2}{3} + \frac{q}{p(1-q)+q} \times \frac{1}{3}\right] Y^+(e_A, e_B),$$

where efforts e_A and e_B were made on date 2 (analyzed later). Alternatively, suppose that readers observe that author B (A) makes the first (second) author — denote this publicized non-alphabetic order by a minus sign (−) — and a corresponding output level Y^-. Y^- will be divided by readers into R_A^- and

R_B^-, given to the two authors respectively:

$$R_A^-(e_A, e_B) = \frac{1}{3} Y^-(e_A, e_B),$$
$$R_B^-(e_A, e_B) = \frac{2}{3} Y^-(e_A, e_B).$$

With the $R_A^+(e_A, e_B)$, $R_B^+(e_A, e_B)$, $R_A^-(e_A, e_B)$ and $R_B^-(e_A, e_B)$ of date 3 in mind, we move backward to date 2 to solve for (e_A, e_B). Notice that date 2 has two possible scenarios. There are two "parallel worlds," and which of them comes true depends on whether the team was told on date 1 to follow the alphabetic norm or not:

Scenario NN: (NN is short for "non-norm") The authors were told not to follow the alphabetic norm. In this scenario, authors A and B maximize, respectively,

$$\max_{e_A} q R_A^+(e_A, e_B) + (1-q) R_A^-(e_A, e_B) - \frac{e_A^2}{2},$$
$$\max_{e_B} q R_B^+(e_A, e_B) + (1-q) R_B^-(e_A, e_B) - \frac{e_B^2}{2},$$

where q (respectively, $1-q$) is the probability that author A (respectively, author B) has made a greater contribution on date 3.

Scenario N: (N is short for "norm") The authors were told to follow the alphabetic norm. In this scenario, authors A and B maximize, respectively,

$$\max_{e_A} R_A^+(e_A, e_B) - \frac{e_A^2}{2},$$
$$\max_{e_B} R_B^+(e_A, e_B) - \frac{e_B^2}{2}.$$

We can immediately conclude that for author A, $e_A^{NN} \le e_A^N$, since in Scenario N, author A never has to worry about the possibility of using a non-alphabetic order on date 3. It is important to note that the technology (2) and the identical effort-cost functions across the two authors ensure that the two authors always make equal efforts. Thus, for author B, $e_B^{NN} \le e_B^N$.

Then the expected output on date 2 is lower in Scenario NN than in Scenario N:

$$\mathbb{E} Y^{NN} \equiv q E_q Y^+ + (1-q) E_q Y^- \le E_q Y^+ \equiv \mathbb{E} Y^N. \tag{3}$$

At the core of inequality (3) is

$$E_q Y^+ \ge E_q Y^-. \tag{4}$$

The derivation of inequality (4) is provided in Appendix A1. Intuitively, a publicized non-alphabetic order suggests that author A is believed to contribute less and this belief is credible and self-enforcing. That reduces the team output under a publicized non-alphabetic order relative to the team output under a publicized alphabetic order, namely $E_q Y^+ \geq E_q Y^-$. Given inequality (4), deriving inequality (3) is straightforward, since Scenario NN corresponds to a convex combination of EY^+ and EY^- while Scenario NN corresponds fully to EY^+.[4]

Finally, we move on to date 1. Date 1 is theoretically trivial as it is simply the date that the nature randomly decides, with probability $0 < p < 1$, whether the team follows the alphabetic norm or not. Nevertheless, date 1 is relevant empirically. As empirical researchers, we are among the readers who observe only the team output and its associated order (+) or (−). Our observation of order (+) is associated with an expected output

$$\mathbb{E}(Y \mid \text{observing } (+)) = \frac{p(1-q)}{p(1-q)+q} \mathbb{E} Y^{NN} + \frac{q}{p(1-q)+q} \mathbb{E} Y^{N}. \tag{5}$$

And our observation of order (−) is associated with an expected output

$$\mathbb{E}(Y \mid \text{observing } (-)) = \mathbb{E} Y^{NN}. \tag{6}$$

By inequality (3), we have

$$\mathbb{E}(Y \mid \text{observing } (+)) \geq \mathbb{E}(Y \mid \text{observing } (-)), \tag{7}$$

which is the hypothesis to be tested in our empirical study. Here Y could refer to either quality or quantity of the output.

To recap the intuition, an ex post (i.e. publicized) non-alphabetic order implies a greater contribution made by the alphabetically late person, which ex ante discourages the alphabetically early person to make enough complementary contribution. In other words, the vagueness resulting from following the alphabetic norm mitigates opportunism by incentivizing the two authors equally.

Before proceeding, notice that in the model whether to follow the alphabetic norm is exogenous, assigned by the "nature" with probability p. We believe that this is a reasonable assumption. p can be considered as the intrinsic propensity of the two researchers to follow social norms. We are *not* assuming the author order to be predetermined before authors make efforts. Rather, we conjecture that individual researchers have predetermined attitudes toward the ordering issue and the alphabetic norm in professional collaboration, which is absorbed into a sufficient statistic p.

There might be exogenous factors other than individual attitudes that may affect whether the alphabetic norm is followed. For example, there are anecdotes that the coauthor up for tenure or promotion in the year of (or right after) the publication is more likely to be made the first author. Such factors are arguably random and thus do not differ from p in our model.

The simple model above, built for informing the hypothesis to test, is a variant of Engers et al. (1999) in that we change the timing of events in their setup and derive equilibria under two different

[4]This is another way to explain why letting authors privately randomize their order on a paper is difficult, as found in Ray ⓡ Robson (2018).

scenarios N and NN. Their original model was about endogenously deciding p after efforts were made and contributions were settled. We switch to an exogenous given p — a representation of the team's attitudes towards the ordering issue and the norm, as noted above — and let it realize at the beginning of the game to generate two scenarios connected with the data. We now proceed to describe our data.

3. Data

The data used in this study come from two sources. The first is the table of contents (TOCs) of economics journals. We chose 42 economics journals and downloaded their TOCs from their websites. The 42 journals include the top-30 journals according to the RePEc journal ranking, supplemented by the A+, A and B journals in the Kiel Institute's journal list and the journals where "ambitious economists" published according to Engemann and Wall (2009).[5] The data from their TOCs provide us with paper-level title, length (number of pages), and author names. At the paper level, the length is used to measure the quantity of the research output, while the (RePEc) ranking of the journal where the paper was published is used to measure the quality of the research output. We normalize the (RePEc) ranking values from 1 (*Quarterly Journal of Economics*) to 42 (*Marketing Science*).[6]

Using journal rankings to measure research output quality has several limitations. First, all journal rankings are subject to certain controversies. Second, journal rankings reflect only a relative quality order at a given point in time, such that even if they were without controversy at a given point in time, they are inadequate in measuring research quality over a long time span. Third, for the purpose of our study, the variations to use are ideally at the paper level, whereas journal rankings provide us with variations only at the journal level. Apart from the reduced variations, the use of journal rankings also keeps us from using journal fixed effects in regressions.

To address the limitations of journal rankings as a measure of research quality, we introduce a second data source into this study. We collected paper-level citation counts (hereafter, citations) from Google Scholar. Notice that citations of papers accumulate over time, such that the quality of later published papers are mechanically under-estimated by citations.[7] To address this issue, we choose a sample period with delayed citation collections. Papers in our working sample were published between 1994 and 2014 — a 21 year period — and their citations were collected all at once — four years later — in December 2018. The four-year delay was designed following Aizenman and Kletzer (2011), who found that the citations of the economics papers in the 1995 and 2001 publication cohorts peaked in the fourth year after their publication dates.[8] Also, in our later regressions, we will always include

[5]The RePEc journal rankings can be found at https://ideas.repec.org/top/top.journals.all.html. The Kiel institute's journal list can be found at https://www.ifw-kiel.de/forschung/internal-journal-ranking.

[6]A crucial virtue of the RePEc rankings is its completeness: the RePEc ranks nearly all economics journals published in English. Since the RePEc journal rankings change over time, the ranking values here refer to those listed in July 2015, corresponding to the sample period of this study.

[7]The citation of a newly published paper always starts from zero. Working papers get cited as well. Google Scholar aggregates the citations of a paper's different versions and subtracts double-counted citations from the total citations.

[8]This finding can be located in Figure 1(b) of Aizenman and Kletzer (2011). It has adjusted for the fact that papers published later receive more publications (they used 1956 as the base year).

(publication) year fixed effects.

The list of the 42 journals and their available years are provided in Table A1, where the newest journals have a few missing years. We exclude journal entries without original and independent contributions, such as editorials, award announcements, minutes, announcements, and short comments. There are 55,987 papers in our original dataset. After data cleaning, our sample contains 37,431 papers.[9] The descriptive statistics of our working dataset are reported in Table A2.

Seven percent of papers in our sample do not follow the alphabetic norm. The percentage is stable, as shown in Figure 1, across years (Panel (a)) and fields (Panel (b)). The share appears to be slightly greater in papers that produce a larger quantity of output (i.e. length, Panel (c)) and a better quality of output (i.e. ranking, Panel (d)).

As a reality check, we alphabetically rank the authors on each paper to examine whether the order is more likely to be reversed when coauthors with early alphabetic positions are involved. The alphabetic norm is indeed used more often when alphabetically early authors are involved. We refer to the order of the initials we constructed alphabetically as ex-ante initials of paper authors in Panel (e) of Figure 1. We also check the order of the initials factually shown on papers, namely the ex-post order, and find that papers that do not follow the alphabetic norm are concentrated at the later part of the alphabet. Apart from confirming our priors, these two reality checks deliver another key message: deviance from the alphabetic norm is not limited to the two extremes of the alphabet. Apparently, the phenomenon is not limited to Professors A and Z, but Professors M and N are in the game as well. In Panels (g) and (h), we revert to the relationships between norm deviance and output (quantity and quality) and check their patterns over time. In general, the comparison is stable over time.

We now move on to regression analysis, which can hold various factors constant to isolate the effect of norm deviance.

4. Empirical Results

Baseline. We specify the following regression to examine the effect of norm deviance:

$$Y_{jt} = \beta \cdot Reversed_j + \bar{\gamma}' X_j + \lambda_t + \epsilon_{jt}, \tag{8}$$

where j and t index paper and year, respectively. $Reversed_j$ is an indicator that equals 1 if paper j adopts a non-alphabetic order of authors. X_j is a vector of paper characteristics (discussed later). ϵ_{jt} is the error term. The dependent variable Y_{jt} alternates across paper j's length, journal ranking, and citations in year t. When the dependent variable is either length or citations, we include journal fixed effects in the regression. When the dependent variable is journal ranking (a time-invariant character-

[9] There are 18,426 sole-author papers, and 130 papers with wrongly coded authors names in the TOCs of corresponding journals.

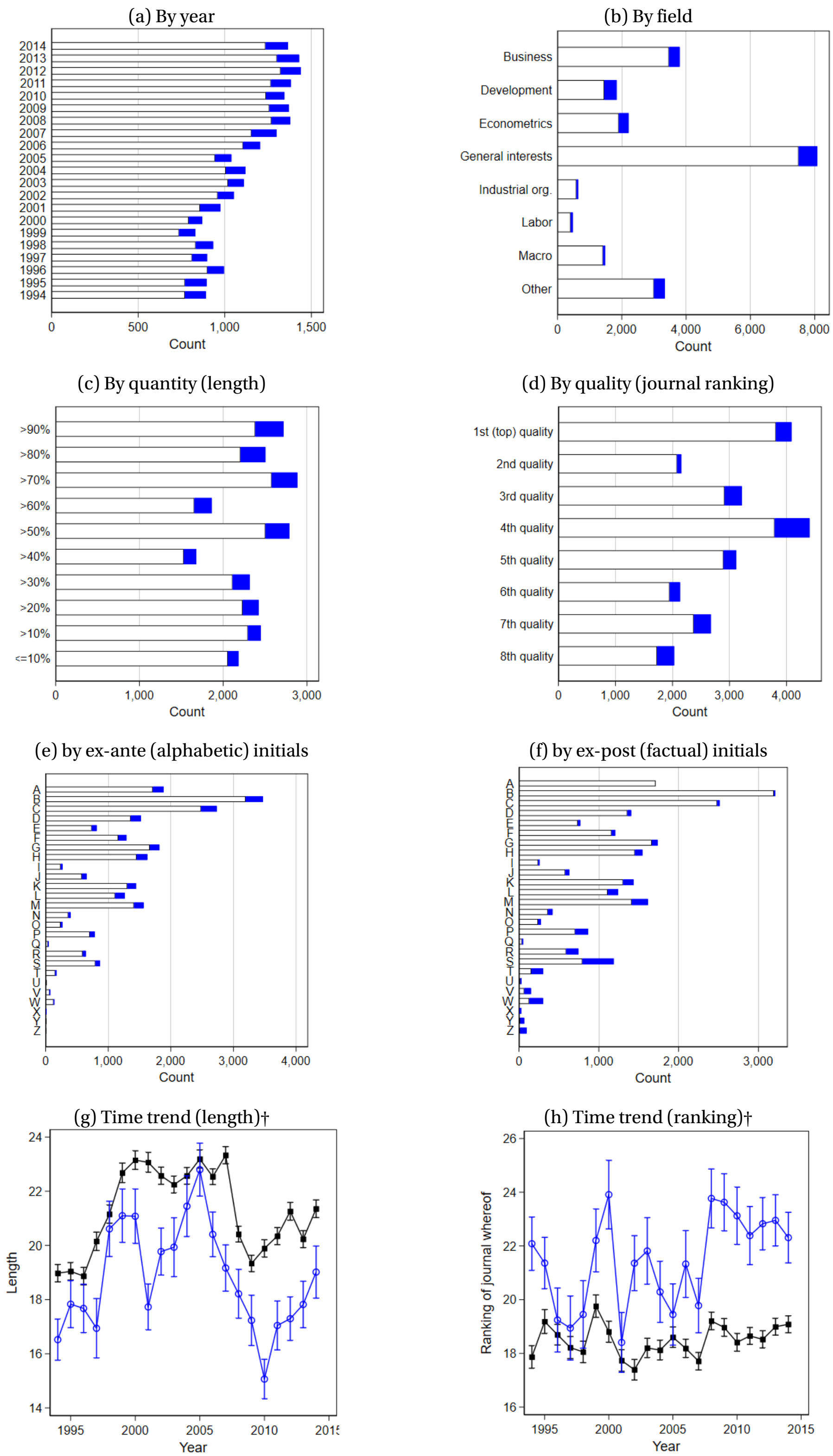

Figure 1: Author Order, Research Output, and Time Trends

† The line connected by squares (in black) corresponds to the alphabetic group, while the line connected by circles (in blue) corresponds to the non-alphabetic group.

istic of journals), we use field fixed effects instead of journal fixed effects.[10] Our parameter of interest is β.

Table 1: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Variable:		ln(Length)			Ranking			ln(Citations)	
Fixed effects:	Journal & Year	Field & Year	Field & Year	Field & Year	Field & Year	Field & Year	Journal & Year	Field & Year	Field & Year
Reversed	-0.037***	-0.138***	-0.124***	2.144***	1.900***	1.741***	-0.096***	-0.070***	-0.021
	(0.011)	(0.026)	(0.025)	(0.558)	(0.555)	(0.507)	(0.027)	(0.026)	(0.029)
Num. of authors	0.006*	-0.010**	-0.025***	0.206**	0.188**	0.441***	0.109***	0.105***	0.131***
	(0.003)	(0.005)	(0.005)	(0.096)	(0.094)	(0.087)	(0.010)	(0.009)	(0.010)
Ranking		-0.005***	-0.001	(NA)	(NA)	(NA)			-0.030***
		(0.001)	(0.002)						(0.001)
ln(Citations)			0.119***			-2.009***	(NA)	(NA)	(NA)
			(0.007)			(0.124)			
ln(Length)	(NA)	(NA)	(NA)		-1.654***	-0.214		0.691***	0.667***
					(0.565)	(0.569)		(0.022)	(0.024)
Observations	37,431	37,431	37,431	37,431	37,431	37,431	37,431	37,431	37,431
R-squared	0.361	0.069	0.143	0.280	0.286	0.329	0.307	0.351	0.307

Robust standard errors in parentheses (clustered at the journal-year level). *** p<0.01, ** p<0.05, * p<0.1.

Our baseline results are reported in Table 1. Among the three dependent variables, we use one at a time. Given any of the three used, we start with a specification that includes only our variable of interest $Reversed$ and one control variable *Number of authors*. Next, we control for one of the other two research output measures. Lastly, we control for both of the other two research output measures. By doing so, we incrementally isolate the association between $Reversed$ and each dimension of research output.

Notice that both journal ranking and citations are measures of quality, such that when either of them is the dependent variable while the other is used as a control variable, the coefficient of $Reversed$ becomes somewhat difficult to interpret. In that scenario, the coefficient captures the impact of $Reversed$ on the residual quality variation not reflected by the controlled quality measure. That being said, when the dependent variable is a quality measure, we prefer not to control for the other quality measure, even though we still report these results in columns (3), (6), and (9) for the purpose of completeness.

Table 1 gives a clear pattern: a deviation from the alphabetic norm is associated with an output weaker in quantity and quality. Specifically, a reversed order is associated with a 3.7 percent shorter length and a 5 percent worse journal ranking (i.e. the ranking value, normalized between 1 (highest ranking) and 42 (lowest ranking), rises by 2.1, $2.1/42 = 5\%$). With the quality (ranking) held constant, the length decrease becomes 13.8 percent. With quantity (length) held constant, the diminished ranking becomes 4.5 percent ($1.9/42 \approx 4.5\%$). When citations are also controlled for, the coefficient of

[10]The field categories are business (including finance, accounting, and marketing), development economics, general interests (treated as a separate field), industrial organization, labor economics, macroeconomics, microeconomics (microtheory), econometrics, and other (including urban, international, environmental, health, and public economics).

Reversed remains in those magnitude ranges (see columns (3) and (6)). As noted above, we prefer columns (2) to column (3), and column (5) to column (6). When quality output is measured by citations, the same direction and a magnitude of 9.6 percent are obtained in column (7). When journal ranking is included to explain citations in column (9), the coefficient of interest becomes statistically insignificant, suggesting some degree of multicollinearity.

The control variables in Table 1 have coefficients consistent with our priors and anecdotes. For example, papers with more coauthors are longer (see column (1)), an association that no longer holds when quality is controlled for (see column (2)). For another example, papers that are longer and published in stronger journals are cited more often (column (9)).

Table 2: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. variable:		ln(Length)			Ranking			ln(Citations)	
Fixed effects:	Journal & Year	Field & Year	Field & Year	Field & Year	Field & Year	Field & Year	Journal & Year	Field & Year	Field & Year
Control variable:§	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel A: Top-5 journals									
Reversed	-0.077+		-0.044				-0.187+		-0.116
	(0.049)		(0.036)				(0.113)		(0.085)
Panel B: Non-Top-5 journals									
Reversed	-0.020**	-0.071***	-0.064***	2.988***	2.813***	2.684***	-0.076***	-0.063**	-0.041+
	(0.010)	(0.012)	(0.012)	(0.393)	(0.372)	(0.365)	(0.026)	(0.025)	(0.026)
Panel C: Field journals									
Reversed	-0.024**	-0.057***	-0.048***	3.640***	3.275***	3.190***	-0.062**	-0.046*	-0.052*
	(0.010)	(0.012)	(0.011)	(0.444)	(0.414)	(0.407)	(0.028)	(0.027)	(0.028)
Panel D: Having two authors									
Reversed	-0.033***	-0.132***	-0.121***	1.791***	1.589***	1.467***	-0.087***	-0.065**	-0.011
	(0.012)	(0.027)	(0.026)	(0.558)	(0.559)	(0.510)	(0.029)	(0.028)	(0.031)
Panel E: Having more than two authors									
Reversed	-0.069***	-0.173***	-0.149***	5.355***	4.946***	4.529***	-0.174***	-0.127**	-0.067
	(0.026)	(0.033)	(0.031)	(0.974)	(0.932)	(0.898)	(0.067)	(0.063)	(0.067)

§ Specifications are the same as in the corresponding columns of Table 1, except in Panel D where the number of authors is not controlled for. Robust standard errors in parentheses (clustered at the journal-year level). *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

We conduct various robustness checks in Table 2. We look into papers published in top-5 journals, non-top-5 journals, field journals (i.e. having general interest journals excluded), with two authors, and with more than two authors. The findings are quite stable. The subsample of papers with more than two authors shows a relatively larger magnitude of the results, indicating a stronger distortion of the incentives within the knowledge-producing team.

The results in Tables 1 and 2 are essentially cross-sectional comparisons. A potential concern is that author order is an outcome of the team formation process that potentially impacts team productivity. We have neither natural experiments that can shock author orders nor lab experiments that can randomize author orders. However, as discussed below, the richness of our data enables us to conduct three econometric experiments that account for endogenous team formation.

Experiment I. An apparent possibility of endogenous team formation is in the initial-letter combination of authors. Professor Z has less incentive to collaborate with others, and when she does collaborate, the alphabetic order is expected to be used less in her collaboration with others. This pattern was first documented by van Praag and van Praag (2008) and we take it into account here. We identify in our sample all possible combinations of last-name initials. For example, consider Professors Robinson and Sanders who published a paper with their names listed alphabetically, and Professors Smith and Ricardo who published a paper with their names listed in a non-alphabetic order. Both pairs of coauthors are recorded under the last name initial combination RS. The fact that Robinson and Sanders chose to follow the alphabetic norm (thereby giving us an observation with $Reverse = 0$), and the fact that Ricardo and Smith chose to deviate from the norm (thereby giving us an observation with $Reverse = 1$) provide us with the variation used in this experiment.

Notice that Robinson and Sanders might choose each other to be collaborators for reasons related to the alphabetic norm, and so might Smith and Ricardo. Our identification strategy in this experiment allows that to happen, but assumes that such considerations are not different between the two pairs. Conceivably, when Professor(s) R chose Professor(s) S, they had the same thoughts about their last-name orders, and vice versa. *For some other reason*, Robinson and Sanders chose the alphabetic order while Professors Ricardo and Smith chose the non-alphabetic order, though those reasons are assumed in this experiment to be irrelevant to the team formation processes "R chose S" and "S chose R."

We find 2,166 last-name initial combinations that appeared more than once in our sample. They cover 35,210 observations, among which 2,691 (7.6 percent) adopt non-alphabetic order. The sample did not shrink substantially because the possible letter combinations in the English alphabet are limited. 64 percent of non-sole author papers have only two authors, and there are only $26^2 = 676$ at most possible letter combinations for the initials of their last names. The results from this experiment are reported in Table 3. In Panel A, we do not use last name initial combination fixed effects such that the coefficients are comparable with those in Table 1. Last name initial combination fixed effects are used in Panel B, where the magnitudes of the effect turn out to be even larger.

Experiment II. We next pinpoint all coauthor teams in our sample. The aforementioned teams {Robinson,Sanders} and {Ricardo and Smith} are now treated as two distinct teams. There are 3,155 such teams in our data, 467 of which used the non-alphabetic order at least once. These teams cover 7,312 papers in the sample, 439 (6.0 percent) of which adopt non-alphabetic orders.

This experiment speaks to the possibility that the teams that have ever used the non-alphabetic order might be systematically different from those that have never used it. In the previous example, {Robinson,Sanders} stick to the alphabetic order, perhaps because they both believe that using last

Table 3: Experiment I (Last Name Initial Combinations)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	ln(Length)		Ranking		ln(Citations)	
Panel A: Without combination fixed effects						
Reversed	-0.040***	-0.119***	2.093***	1.625***	-0.129***	-0.057*
	(0.010)	(0.011)	(0.552)	(0.503)	(0.027)	(0.029)
Ranking		-0.001*		(NA)		-0.031***
		(0.000)				(0.001)
ln(Citations)		0.118***		-2.003***		(NA)
		(0.003)		(0.125)		
ln(Length)		(NA)		-0.216		0.669***
				(0.570)		(0.024)
Fixed effects	Journal & Year	Field & Year	Field & Year	Field & Year	Journal & Year	Field & Year
Observations	35,210	35,210	35,210	35,210	35,210	35,210
R-squared	0.361	0.142	0.279	0.328	0.306	0.305
Panel B: Wth combination fixed effects						
Reversed	-0.153***	-0.146***	2.504***	2.144***	-0.159***	0.048+
	(0.013)	(0.013)	(0.261)	(0.252)	(0.032)	(0.030)
Control variables§	No	Yes§	No	Yes§	No	Yes§
Observations	35,210	35,210	35,210	35,210	35,210	35,210
R-squared	0.083	0.158	0.085	0.181	0.087	0.249

Robust standard errors in parentheses (clustered at the combination-year level). *** p<0.01, ** p<0.05, * p<0.10,+p <0.15.

§ Specifications are the same as in the corresponding columns of Panel A. To save space, only the coefficient of the revsersed indicator is reported.

names is the only fair way to order authors. This attitude towards fairness might be different from {Ricardo and Smith}, who think the alphabetic order is unfair for Smith, such that they should alternate the order across projects. Such differences in attitudes may generate cross-team differences in many ways that relate to research output. For example, the order-alternating team {Ricardo and Smith} emphasizes individual contributions to the project, while the order-invariant team {Robinson,Sanders} emphasizes collective efforts.

To address the above possibility, we now add an indicator variable $Ever\ Reversed$ that equals 1 when the team uses the non-alphabetic order at least once. We are interested in whether it influences research output, and if so, whether it absorbs the variations in the original $Reversed$ — in other words, whether the reduced outputs of non-alphabetic papers reflect a reduced team performance or a reduced project performance.

The results are reported in Table 4, where the sample is limited to the 7,312 papers published by our identified teams. Panel A focuses on the original variable of interest $Reversed$, Panel B uses the new variable $Ever\ Reversed$ instead of $Reversed$, and Panel C includes both variables. Evidently, a deviance from the alphabetic norm reduces both team-level and project-level performances. In particular, the project-level effect remains when the team-level effect is controlled for (see Panel C).

Table 4: Experiment II (Sample of Teams)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. variable:		ln(Length)			Ranking			ln(Citations)	
Fixed effects:	Journal & Year	Field & Year	Field & Year	Field & Year	Field & Year	Field & Year	Journal & Year	Field & Year	Field & Year
Panel A: Reversed project									
Reversed	-0.072**	-0.191***	-0.163***	2.353***	1.780***	1.538***	-0.186***	-0.131**	-0.070
	(0.029)	(0.035)	(0.033)	(0.553)	(0.540)	(0.527)	(0.063)	(0.060)	(0.059)
Ranking		-0.009***	-0.004***	(NA)	(NA)	(NA)			-0.032***
		(0.001)	(0.001)						(0.002)
ln(Citations)			0.140***			-1.893***	(NA)	(NA)	(NA)
			(0.006)			(0.097)			
ln(Length)	(NA)	(NA)	(NA)		-2.681***	-1.168***		0.766***	0.712***
					(0.208)	(0.220)		(0.032)	(0.028)
Observations	7,312	7,312	7,312	7,312	7,312	7,312	7,312	7,312	7,312
R-squared	0.391	0.082	0.173	0.394	0.409	0.445	0.351	0.405	0.366
Panel B: Reversed team (ever had a reversed project)									
Ever reversed	0.033	-0.141***	-0.124***	2.082***	1.647***	1.507***	-0.016	-0.042	-0.020
	(0.025)	(0.030)	(0.028)	(0.547)	(0.554)	(0.538)	(0.058)	(0.056)	(0.057)
Ranking		-0.010***	-0.004***	(NA)	(NA)	(NA)			-0.033***
		(0.001)	(0.001)						(0.002)
ln(Citations)			0.141***			-1.896***	(NA)	(NA)	(NA)
			(0.006)			(0.097)			
ln(Length)	(NA)	(NA)	(NA)		-2.698***	-1.178***		0.768***	0.714***
					(0.209)	(0.221)		(0.032)	(0.028)
Observations	7,312	7,312	7,312	7,312	7,312	7,312	7,312	7,312	7,312
R-squared	0.390	0.079	0.172	0.393	0.409	0.445	0.351	0.405	0.366
Panel C: Both									
Reversed	-0.103***	-0.158***	-0.132***	1.765***	1.299**	1.079*	-0.214***	-0.136**	-0.074
	(0.032)	(0.038)	(0.035)	(0.615)	(0.590)	(0.576)	(0.069)	(0.065)	(0.064)
Ever reversed	0.074***	-0.078**	-0.071**	1.367**	1.126*	1.075*	0.068	0.012	0.009
	(0.028)	(0.032)	(0.031)	(0.609)	(0.606)	(0.589)	(0.064)	(0.061)	(0.061)
Ranking		-0.009***	-0.004***	(NA)	(NA)	(NA)			-0.032***
		(0.001)	(0.001)						(0.002)
ln(Citations)			0.140***			-1.892***	(NA)	(NA)	(NA)
			(0.006)			(0.097)			
ln(Length)	(NA)	(NA)	(NA)		-2.664***	-1.153***		0.765***	0.712***
					(0.209)	(0.220)		(0.032)	(0.028)
Observations	7,312	7,312	7,312	7,312	7,312	7,312	7,312	7,312	7,312
R-squared	0.392	0.083	0.174	0.394	0.410	0.446	0.351	0.405	0.366

Robust standard errors in parentheses (clustered at the team-year level). *** p<0.01, ** p<0.05, * p<0.10.

Experiment III. Our third experiment uses the sample from Experiment II but the estimation technique from Experiment I. That is, we add team fixed effects to the team sample. By doing so, we hold all team-specific characteristics of a team constant across the projects (papers) of the team.

The results are reported in Panel A of Table 5. A deviance from the alphabetic norm turns out to be associated with shorter papers, but does not significantly relate to weaker journal rankings or fewer

Table 5: Experiment III (Team Fixed Effects)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	ln(Length)		Ranking		ln(Citations)	
Panel A: All						
Reversed	-0.203***	-0.172***	-0.033	0.293	-0.171*	-0.021
	(0.056)	(0.052)	(0.786)	(0.726)	(0.102)	(0.093)
Control variables§	No	Yes	No	Yes	No	Yes
Observations	7,312	7,312	7,312	7,312	7,312	7,312
R-squared	0.650	0.697	0.780	0.795	0.770	0.807
Panel B: Upper half journal ranking standard deviations						
Reversed	-0.226***	-0.219***	-0.011	0.933	-0.041	0.117
	(0.076)	(0.070)	(1.366)	(1.200)	(0.136)	(0.119)
Control variables§	No	Yes	No	Yes	No	Yes
Observations	3,555	3,555	3,555	3,555	3,555	3,555
R-squared	0.499	0.561	0.520	0.569	0.664	0.722
Panel C: Top 10 percent journal ranking standard deviation						
Reversed	-0.030	0.038	7.270*	2.841	-0.602**	-0.427**
	(0.127)	(0.131)	(4.066)	(3.221)	(0.233)	(0.217)
Control variables§	No	Yes	No	Yes	No	Yes
Observations	704	704	704	704	704	704
R-squared	0.517	0.562	0.148	0.372	0.654	0.723

§ Control variables are the other two output measures. To save space, only the coefficient of the revsersed indicator is reported. Team fixed effects are used in all columns. Robust standard errors in parentheses (clustered at the team level). *** p<0.01, ** p<0.05, * p<0.1.

citations when control variables are used. Since the research output has two margins, the research output of a given team may decrease at one margin but not at the other. That is, when lowering output, some teams choose to target shorter papers but do not target weaker journals, while others opt for weaker journals but do not shorten their papers. Both types of teams are common in reality, though we suspect that the journal tiers targeted by a given team are less volatile than the length of the team's papers. In other words, journal-tier choices have a stronger tendency to be a fixed effect of a team in comparison with paper-length choices.

To examine whether the relative stability in journal-tier choices at the team level explains the statistically insignificant coefficients in Panel A, we next calculate the standard deviation of each team's journal rankings (JRSD) across its projects in order to differentiate the two margin choices. A greater JRSD suggests that the team publishes in more diverse journals.

Panel B uses the subsample of teams with the upper 50 percent JRSD, the results of which are similar to those from the full sample in Panel A. Then Panel C uses the subsample of teams with the top 10 percent JRSD, where the quality margin becomes statistically significant while the quantity margin becomes statistically insignificant. This change has three implications. First, when we intentionally raise the variation along the quality margin, the variation along the quantity margin shrinks. This supports our conjecture that there exist two margin choices, and boosting the variation at one margin automatically shrinks the variation at the other. Second, the intentionally raised quality margin demonstrates results consistent with our thesis on the alphabetic norm — a deviance from the alphabetic norm *weakens* quality. Notice that moving from Panel A to Panel C artificially increases the variation in journal rankings, but does not artificially raise the correlation between journal ranking and $Reversed$. Third, there is also a negative association between citations and $Reversed$. This negative association must not be driven by the artificial sample change from Panel A to Panel C. Notice that the ranking-based results are less significant than the citation-based results, which is not surprising because journal rankings as a quality measure, by construction, have less variation than paper-level citations as a quality measure.

5. Conclusions

Economists are known to emphasize individual incentives, although they have a norm of ordering authors alphabetically in publications. This is a rational choice when information asymmetry is taken into account. Specifically, a deviance from the norm does more harm than good to the team incentives and thus to the team outputs. We find that research teams produce less output, both quantitatively and qualitatively, when they do not follow the alphabetic norm. This illustrates that the incentives in a team hinge on the norms of the society where the team operates. A deviance from social norms reduces output through distorting incentives in the team.

We find two questions that have yet to be answered in this study and leave them as avenues for future research. On the theoretical front, it remains unclear why the alphabetic norm is well-established in economics but not in other disciplines. This difference in professional norms might be related to research resource inequality (such as grants), which is relatively small in economics. Our study takes the alphabetic norm as given and proceeds directly to the incentives underlying the norm. On the empirical front, we collected data from the past when randomizing author orders was not an option. Beginning in 2019, randomized author orders have become certifiable through the American Economic Association. Future journal data with the randomization option will prove tremendously useful in understanding the teamwork incentives in this profession.

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Appendices (for online publication only)

A1. Derivation of Inequality (4)

Given functions (1) and (2), readers assign credits and authors make efforts as follows.

Conditional on observing a publicized non-alphabetic order (−), readers give a third of the output (credit) to author A. That is, $R_A^-(e_A, e_B) = \frac{1}{3} Y^-(e_A, e_B)$. In this case, author A maximizes $\frac{1}{3} x_A - \frac{e_A^2}{2}$ by setting $e_A^- = \frac{1+\bar{\mu}}{3}$. Accordingly, author B sets $e_B^- = \frac{1+\bar{\mu}}{3}$. They make the same level of effort, as dictated by the production technology. So the ex-post output is

$$Y^- = \min\{\frac{1+\bar{\mu}}{3} + \mu_A, \frac{1+\bar{\mu}}{3} + \mu_B\}, \tag{A.1}$$

whose value depends on the realized μ_A and μ_A. Notice that the publicized non-alphabetic order (−) conveys (1) that the authors were told by the nature not to follow the alphabetic norm on date 1, and (2) that author B has less contribution than author A.

Conditional on observing alphabetic order (+), readers know that the two authors make the same level of effort, but do not know their contributions. Specifically,

1. With probability $\frac{p(1-q)}{p(1-q)+q}$, author A has a smaller contribution and thus receives 1/3 of the output, while author B has a greater contribution and thus receives 2/3 of the output. Given this case, the effort levels are $(e_A^+ = \frac{(1+\bar{\mu})}{3}, e_B^+ = \frac{2(1+\bar{\mu})}{3})$. We refer to the resulting ex-post output as

$$Y^{+1} = \min\{\frac{(1+\bar{\mu})}{3} + \mu_A, \frac{2(1+\bar{\mu})}{3} + \mu_B\}, \tag{A.2}$$

   whose exact value is unknown but clearly $E\,Y^{+1} \geq E\,Y^-$, where Y^- is from equation (A.1).

2. With probability $\frac{q}{p(1-q)+q}$, author A has a greater contribution and thus receives 2/3 of the output, while author B has a smaller contribution and thus receives 1/3 of the output. Given this case, the effort levels are $(e_A^+ = \frac{2(1+\bar{\mu})}{3}, e_B^+ = \frac{(1+\bar{\mu})}{3})$. We refer to the resulting ex-post output as

$$Y^{+2} = \min\{\frac{2(1+\bar{\mu})}{3} + \mu_A, \frac{(1+\bar{\mu})}{3} + \mu_B\}, \tag{A.3}$$

   Once again, the exact value is unknown but $E\,Y^{+2} \geq E\,Y^-$.

Recall that, upon observing an alphabetic order, the expected output is

$$E_q Y^+ \equiv \frac{p(1-q)}{p(1-q)+q} Y^{+1} + \frac{q}{p(1-q)+q} Y^{+2}. \tag{A.4}$$

Combining equations (A.2), (A.3), and (A.4), we have

$$E_q Y^+ \geq E_q Y^-. \tag{A.5}$$

A2. Appendix Tables (see the next page)

Table A1: List of Journals

Journal name	Number of years available
American Economic Journal: Applied Econ*	6
American Economic Review	21
Econometric Theory	21
Econometrica	21
Economic Journal	21
European Economic Review	21
Games & Economic Behavior	21
International Economic Review	21
Journal of Accounting & Economics	21
Journal of Applied Econometrics	21
Journal of Banking & Finance	21
Journal of Business & Economic Statistics	21
Journal of Development Economics	21
Journal of Econometrics	21
Journal of Economic Behavior & Org	21
Journal of Economic Growth**	19
Journal of Economic Theory	21
Journal of Finance	21
Journal of Financial Economics	21
Journal of Human Resources	21
Journal of Industrial Economics	21
Journal of International Economics	21
Journal of Labor Economics	21
Journal of Law & Economics	21
Journal of Law, Economics & Organization	21
Journal of Monetary Economics	21
Journal of Money Credit & Banking	21
Journal of Political Economy	21
Journal of Public Economics	21
Journal of Risk & Uncertainty	21
Journal of Urban Economics	21
Journal of the European Econ Association***	12
Marketing Science	21
Oxford Economic Paper	21
Quarterly Journal of Economics	21
Rand Journal of Economics	21
Review of Economic Dynamics****	17
Review of Economic Studies	21
Review of Economics & Statistics	21
Review of Financial Studies	21
Scandinavian Journal of Economics	21
World Development	21

The starting year of the journal: * 2009, ** 1996, *** 2003, **** 1998.

Table A2: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Length (pages)	37,431	21.03	10.67
Ranking, original	37,431	28.01	28.10
Ranking, relative	37,431	18.67	11.58
Reversed (0 or 1)	37,431	0.07	0.26
Num. of authors	37,431	2.44	0.71
Year	1994 to 2014 (up to 21 years)†		
Journals	42†		

† See Table A1 for details.