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Norms and Team Formation: Evidence from Research Partnerships*

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Abstract

Scientific, artistic, and professional work is increasingly performed in groups. In this study, we seek to understand the extent to which norms influence the composition of such groups. In particular, we analyze the effect of the alphabetical norm in academic citations on the composition of research teams in economics. First, we present a model of endogenous team formation given the alphabetical norm and analyze the effect of the norm on the desirability of any two individuals to conduct a joint project. We then examine the last names of co-authors from nearly 100 academic journals and find a significant difference between the matching behavior of authors who obey the alphabetical norm relative to authors who violate the norm. We interpret this finding as evidence that the alphabetical norm results in distortion of the composition of research teams.

JEL Classification: A11, A13, J70, Z13.

Keywords: Team Formation, Norms, Academic Publishing.

1 Introduction

The era of lone scientists and solitary creators is over. Teams have taken over creative and scientific activity; collaboration is the word of the moment.¹ Evidence of increased collaboration over the long-term can also be found outside of scientific professions, from law firms in the professional sphere to cinema in the artistic domain. Yet, little is known about the process through which individuals form teams and which factors influence them.

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¹To give but one illustrative example: In a 2009 Research!America online survey of 800 U.S. adults in which individuals were asked to name one living scientist, 65% failed to produce any answer and over 20% gave the name of a deceased scientist with responses including Albert Einstein (4%), Marie Curie (2%), and Louis Pasteur (2%).

It is apparent, for example, that social and professional norms play a role in the way in which groups are formed. However, establishing a causal link between norms and the distribution of realized teams is difficult because it is rare for a norm, such as the favoring of an individual characteristic, to be unrelated to that individual's ability to contribute to the potential success of the group in its mission. Consider, for instance, the recent controversy regarding wage disparity between male and female actors in Hollywood.² While this difference may reflect a norm of paying males higher salaries, it is also possible that it reflects a difference in the value added to a movie by male actors relative to the value added by female actors. If these differences vary depending on the composition of the team (e.g. the compensation of a female actor is higher when paired with other female actors), the distribution of realized matches (i.e. which actors cast together) would be significantly affected. Similar issues arise in many industries in which compensation depends on exogenous characteristics like age, racial background or country of origin.³

We seek to overcome this difficulty by examining the effect of the alphabetical norm on the composition of co-author teams in the field of economics. The widespread norm in the academic economics literature is to list co-authors in alphabetical order according to each co-author's last name. We posit that (i) (at least some) individual authors have a preference to be listed first and, therefore, account for this consideration (amongst others) when choosing a co-author and (ii) ability is uncorrelated with alphabetical prominence.

The first assumption is supported by literature in the cognitive sciences and by direct evidence from the economics discipline. It has been widely documented that individuals will choose to devote their attention to the first item in a list with a higher frequency than any subsequent item.⁴ Similarly, a large literature in cognitive sciences has provided evidence of the so-called *serial position effect*, which is the tendency for individuals to recall the first item (referred to as the primacy effect) and the last item (referred to as the recency effect) to approximately the same degree, whereas intermediate items are recalled to a lesser degree. However, individuals examined in this latter branch of studies are typically compelled to read all items in the list. Considering that the former branch of literature suggests that when given a choice, individuals devote their attention to the first item most frequently, it follows that readers will remember the first co-author more readily than a subsequent co-author. Since success in academic disciplines is intimately related to reputation and name recognition, first authors may receive disproportionately large credit for their work. This indeed is supported by direct evidence that a non-trivial minority of co-authors in economics are not ordered alphabetically despite the existence

 $^{^2 {\}rm For}$ example, see the February 23, 2015 article on the website *Slate* entitled, "The Gender Wage Gap Is Especially Terrible in Hollywood."

 $^{^{3}}$ See Dustmann, Glitz, and Schönberg (2011) for evidence on assortative matching of immigrants across firms based on their nationality of origin.

⁴For example, see Rubinstein and Salant (2006) and references therein.

of the alphabetical order norm.⁵

Therefore, it stands to reason that in addition to considering a prospective co-author's ability to substantively contribute to an article, a researcher in economics seeking a coauthor may also take into account the prospective co-author's last name. Given that the order of an individual's last name in the alphabet is unlikely to be correlated with their ability as an economist, by examining the correlation of last name alphabetical ranks across co-author teams in economics we may assess whether the convention of listing coauthors in alphabetical order influences the composition of research teams in economics.

In an academic discipline in which the alphabetical convention prevails, the distribution of realized co-author relations will depend on the specific details of the process through which ideas develop into papers. In order to establish this link we develop a simple model of random matching, where individuals differ in their names and the match quality is independently and identically distributed across matches. In this setup, individuals ranked at the end of the alphabet (to whom we will refer as occupying a low alphabetical rank) might be willing to work on an idea of a given quality on which an individual that is ranked higher in the alphabet would not consider working. That is, individuals at the beginning of the alphabet might have a higher reservation value for their time (in equilibrium). For example, Ms. Yeats will have relatively fewer opportunities to be a first co-author relative to Mr. Dundee, and therefore Mr. Dundee can be pickier regarding projects on which he would work as a first co-author (and as a second co-author) than Ms. Yeats. Thus, conditional on holding a certain position, the lower the rank of one's name, the larger the range of ideas he will be willing to consider.

In this world, we would expect a negative correlation in the distribution of names of those co-authors who obey the alphabetical norm. A simple example can illustrate why this would be the case. Consider a world in which there are only four authors: Mr. Dundee, Ms. Espinoza, Ms. Yeats, and Mr. Yu. The minimum (or reservation) idea quality of a given project on which each individual is willing to work is listed in Table 1. These values are consistent with the notion that the minimum idea quality on which an individual is willing to work increases with the alphabetical rank of the individual's last name (an equilibrium result) and with the assumption that the minimum idea quality on which an individual with a given last name is willing to work is lower as a first co-author than as a second co-author. The equilibrium result is consistent with the idea that higherranked individuals in the alphabet have a higher reservation value for their time and the assumption is consistent with the notion that a given individual would prefer to be listed as a first co-author rather than as a second co-author.

Given these four authors, we have the following three matching possibilities: (1) Dundee-Espinoza and Yeats-Yu, (2) Dundee-Yeats and Espinoza-Yu, and (3) Dundee-

⁵See also Maciejovsky, Budescu, and Ariely (2009) for evidence on the primacy effect in the field of economics.

Yu and Espinoza-Yeats (see Table 2). If these individuals randomly match, the average alphabetical distance of these three pairs will be 5/3. However, if these authors obey the alphabetical norm and they only work on an idea that meets or exceeds their reservation idea quality threshold, then it is less likely that the first match will occur. This is because Dundee-Espinoza will not match for an idea quality that is less than 12, whereas each of the pairs that comprise the second and third matching possibilities will work an idea associated with a minimum quality of 10. Therefore, on average, the alphabetical distance between co-authors in this scenario will exceed the alphabetical distance between co-authors when they are matched randomly. More generally speaking, pairs of co-authors which are more distant from one another in alphabetical rank will be more likely to co-author with each other than pairs of co-authors which are more proximate to each other in alphabetical rank.⁶

Now let us consider the matching process of co-authors who violate the alphabetical norm. For these pairs of co-authors, the individual with the lower-ranked last name is listed as the first co-author for one of several possible reasons. For example, as the paper develops it may become clear that she is more integral to the success of the paper. In some of these cases, these co-authors will match for such a reason and then switch order prior to submitting for publication. In other cases, their violation of the alphabetical norm provides evidence that they matched solely due to the fact that they viewed each other as an optimal match. In particular, the lower-ranked author (who is listed first) will face a distribution of co-authors whose higher-ranked last names are independent of talent, and the higher-ranked author (who is listed second), conditional on being willing to serve as a second co-author, has no preference for the last name of his co-author. Therefore, we expect that the last names of co-authors who violate the alphabetical norm will be less negatively correlated with one another than authors who obey the alphabetical norm.

It is important to note that, regardless of how matching occurs, correlations between co-author last names may exist if names in a particular region of the world are not uniformly distributed and individuals are more likely to match with someone who lives in the same region (which we shall refer to as a *community*).⁷ In order to address this issue, we exploit the subset of co-authors in our data who violate the alphabetical norm. We shall argue that this subset of co-authors will allow us to identify the effect of the norm on those who obey it.

In particular, we assume that for a given individual, the propensity of participating in an article that violates the alphabetical norm is uncorrelated with the distribution of names among her potential collaborators. In particular, this assumption implies that the

 $^{^{6}}$ In this simple example we have assumed that reservation utilities are exogenous. In reality, however, they depend on the equilibrium distribution of matches. In Section 3 we present a simple model of team-formation that takes this issue into account.

⁷In particular, the existence of both of these conditions is likely to drive the correlation of co-author names upward for reasons we will address later in the study.

extent to which switching occurs does not differ across different communities. Therefore, even if correlations between co-author last names exist due to a non-uniform distribution of names in a particular community and a proclivity of individuals to choose co-authors within their own community, we do not expect these effects to differ when comparing coauthors who conform to the alphabetical norm and co-authors who violate the alphabetical norm.

Employing this strategy for purposes of identifying the effect of the alphabetical norm on the composition of research teams, we compare the correlation of co-author last names who obey the norm with the correlation of co-author last names who violate the norm using data collected from 91 of the top 100 ranked journals in the field of economics throughout the history of each journal. There exist over 180,000 articles in this sample, and nearly half of these articles were authored by at least two individuals. This leaves us with a large sample of co-author partnerships with which we may examine the effect of the alphabetical norm on research team composition.

Our empirical results suggest that strategic matching is indeed prevalent in the data. We show that the average distance in the names of co-authors of two-authored and threeauthored papers which respect the alphabetical order is significantly higher than that of those authors in articles which do not respect this norm. These results are robust to different specifications and are strongest for papers published in top-tier journals. We interpret this finding as evidence that the utility associated with being listed first on an article influences the realized distribution of co-authors.

Related Literature

This paper contributes to a number of strands of the literature. First, there is a an important literature analyzing team-production and team-formation, and, in particular, the role of incentives in shaping those teams. Isolating the effects of team-formation and effort provision in team-production has proven difficult to tackle for empirical economists. First of all, participation is endogenous and the researcher often does not observe the counterfactual population of potential members (Lazear (2000)). Secondly, individual input provision in teams is often hard for the researcher to measure.⁸ Finally, rewards may depend on unobservable characteristics or may be endogenous to team performance (Chiappori and Salanié (2002), Prendergast (1999)). Several attempts have been made in order to tackle these issues. Lazear (2000) conducted a field study in the Auto Glass Industry and established that selection accounts for a large share of the productivity gains brought about by stronger incentives. Bandiera, Barankay, and Rasul (2005) and Bandiera, Barankay, and Rasul (2010) carried out a field experiment in a fruit farm in order to provide evidence of the role of peers and other organizational design features

 $^{^{8}}$ According to Alchian and Demsetz (1972) this is one of the defining features of team-production.

on productivity.⁹ Our work provides causal evidence of the link between incentives and team-formation in the long-run outcome of a natural, high-stakes environment.

We also contribute to a more specific literature that analyzes academic publishing, with a special focus on Economics. Engers, Gans, Grant, and King (1999) provide a model of team production that rationalizes the alphabetical rule as the outcome of negotiation between both authors when individual contributions are unobserved. Our model abstracts from effort provision and focuses instead on the formation of partnerships, providing a new channel through which the attribution of merit determines final output.¹⁰ Einav and Yariv (2006) and Van Praag and Van Praag (2008) show that names matter in the academic market for economists. In particular, they show that individual authors whose name is ranked higher in the alphabet have more prolific careers, are more likely to get tenure and receive more citations. Maciejovsky, Budescu, and Ariely (2009) provide experimental evidence that individuals beliefs about relative contribution of authors to a research paper are shaped by the prevailing norm within their field. We use these studies as the starting point of our inquiry and develop the theme further by providing evidence that individual authors take this advantage into account when forming research teams. Indeed, we show that their estimates of the advantage of having a high-ranked name (and, therefore, being listed as a first co-author with higher probability) may be conservatively low because potential collaborators at the beginning of the alphabet are less likely to work on an idea of a given quality than collaborators at the end of the alphabet.

Finally, there is a large literature in Economics and Economic History that uses names as a data source.¹¹ The closest paper to ours is Esteve-Volart and Bagues (2012) which provides evidence of strategic nomination of candidates by political parties in Spanish Legislative Elections. Positions in the ballot are distributed according to the alphabetical order and political parties tend to choose female candidates with lower-ranked names so as to satisfy gender quota restrictions while ensuring that most male candidates get elected.

The remaining of the paper is organized as follows. Section 2 briefly described the data we use. Section 3 presents a simple model in the spirit of the marriage market literature that establishes a link between the alphabetical norm and the distribution of co-authors' names. Section 4 discusses assumptions of the model as well as our identification strategy. Section 5 provides the empirical results and Section 6 concludes.

⁹See also Ytsma (2015) which shows that the introduction of stronger pay-for-performance incentives improved sorting across academic institutions in Germany. For a survey see Bandiera, Barankay, and Rasul (2011)

 $^{^{10}\}mathrm{See}$ Section 6 for a discussion of the convenience of the alphabetical rule.

¹¹Recent examples include Güell, Mora, and Telmer (2015) and Olivetti and Paserman (2015)

2 Data

We have compiled a data set including all articles from 91 of the top 100 journals in economics (according to Kalaitzidakis, Mamuneas, and Stengos (2003)).¹²¹³ Summary statistics are contained in Table 3. In total we have 182,745 articles, out of which 98,250 have only one author. Two-authored and three-authored articles are increasingly prominent over time and account for 46% of the total number of observations.¹⁴ Out of these, 67,728 (approximately 81%) respect the alphabetical order in listing the names of the authors. Importantly, 584 articles contain at least two authors with the same last name. We refer to them as *exact matches* and we will typically exclude them from our empirical analysis since it is usually the case that authors are related to each other through some family connection.¹⁵

In order to carry out our empirical exercise, we assign a number to each last name that corresponds to the proportion of names in the sample that dominate it in the lexicographic order. A number of considerations are in order. First, names appearing multiple times receive the same ranking in each case. Second, in order to compute the proportion of names preceding a certain name, we count each name as many times as it appears in the sample. For instance, if there were 1,000 articles in the sample, each with two authors, and the highest-ranked name in the sample was Abbot, it would receive a ranking of 0.0005. If Abbot only appears once, then the second name (say Abreu) would receive a ranking of 0.001, while if Abbot appears five times, Abreu would receive a ranking of 0.003. Since the ranking is made based on last names only, we do not distinguish between two authors with the same last name.¹⁶

3 Model

We now present a simple model of endogenous team formation in the spirit of the marriage market literature, with heterogeneous types and non-transferable utility (Burdett and

 $^{^{12}}$ See Table 4 for the complete list of journals and disaggregated statistics.

¹³This is perhaps the most widely used ranking in economics, but certainly not the only one. A particularly unfortunate shortcoming of this list is that it excludes new journals such as the American Economic Journals and the new Journals of the Econometric Society.

¹⁴We do not analyze approximately 2,000 two-author papers and approximately 2,000 three-author papers in which a non-alphabetical symbol occupies one of the first five places in the author's last name. Some of these symbols are data conversion errors from the journal source to EconPapers whereas in other cases, the symbol is part of the author's last name (an apostrophe, for example). Software arbitrarily chooses an alphabetical rank for such symbols, and inspection of each instance in order to detect errors would have been particularly time-consuming. We have no reason to believe that the alphabetical distances associated with these authors to be different than in the remainder of the sample.

¹⁵While proving the connection is often hard, when we randomly rematched all pairs we only obtained 10 matches in which co-authors share the same last name.

¹⁶See Subsection 5.4 for a robustness check including both first names and exact matches. The results in this case are, if anything, stronger.

Coles, 1997). The purpose of this model is to clarify our identification method and provide testable implications for our empirical results.

We consider an economy with a large number of individuals (authors) $i \in N$. Each individual i has a name $x_i \in [0, 1]$. Individuals need to match in pairs to produce papers. In each period t = 1, 2, ... idle individuals meet each other randomly and observe their match value v distributed according to F(v). If both individuals agree to form the match, they start the project. If one of the individuals rejects, both individuals remain unmatched and do not produce in the present period. Projects end according to a Poisson process with mean λ . Let i and j form a match and let v_{ij} be the match value. This value is shared among authors according to the alphabetical order, so that individual i receives αv_{ij} if $x_i < x_j$ and $(1 - \alpha)v_{ij}$ otherwise, with $\alpha \ge 0.5$. Individuals discount the future by δ . Let v(x) be the cutoff strategy used by an individual with name x so that she accepts projects that give her utility at least x whenever she is the second coauthor and always accept articles as a first author.¹⁷ Let $\mu(z)$ be the distribution of names in the pool of idle individuals. We are now in the position to define a Stationary Equilibrium for this economy.

Definition 1. An Equilibrium is a distribution $\mu(z)$ and a cutoff function v(z) such that every agent with name z maximizes her utility by accepting a match as a lower-ranked individual if and only if $v \ge v(z)$ and $\mu(z)$ is such that

$$\mu'(z)(\mu(z)(1 - F(v(z))) + \int_{z} (1 - F(v(y)))d\mu(y)) = (1 - \mu'(z))\lambda$$
(1)

In an Stationary Equilibrium, we can write the maximization problem of a given individual as a recursive problem. The value function of an unmatched individual with name x is

$$U(x) = x \int_{v(x)} V_2(y;x) dF(y) + \int_x^1 \int_{v(z)} V_1(y;x) dF(y) d\mu(z) + \delta \left\{ xF(v(x)) + \int_x^1 F(v(z)) d\mu(z) \right\} U(x)$$

where $V_k(y; x)$ is the value of an individual named k who is listed in the k - th position in a team with match quality y as defined in

$$V_1(y;x) = \alpha y + \delta((1-\lambda)V_1(0;x) + \lambda U(x))$$
(2)

and

$$V_2(y;x) = (1-\alpha)y + \delta((1-\lambda)V_2(0;x) + \lambda U(x)).^{18}$$
(3)

These equations are easy to interpret. The utility earned by an individual in a team

 $^{^{17}}$ In Lemma 1 we establish that this strategy constitutes an equilibrium of the game. It is also easy to prove that there are no (stationary) equilibria in which the second author is willing to form a match but the first author is not.

¹⁸Notice that $V_1(0; x) = V_2(0; x)$.

with match value y is found by adding her corresponding share of the proceedings to the continuation value. This future payoff depends on whether the project is completed immediately (so that the individual becomes unmatched) or takes longer (so that the individual remains in the match but does not produce additional output). By definition of the cutoff strategy, it must hold that an individual who is indifferent between accepting or rejecting a project earns a continuation value $V_2(v(x); x) = U(x)$. Hence from (3),

$$(1 - \alpha)v(x) = \frac{U(x)}{1 - \delta(1 - \lambda)} \tag{4}$$

The following Lemma establishes useful properties of U(x).

Lemma 1. U(x) is a decreasing function of x. Further, $U(0) \leq \frac{\alpha}{1-\alpha}U(1)$ so that if the second author agrees to form a match, the first author will always be willing to accept.

As a result v(x) is decreasing in x. This implies that the probability that i and j match upon meeting equals $1 - F(v(x_j))$ whenever $x_i < x_j$. Notice that $\mu'(z)$ is decreasing in zso that individuals with higher-ranked names are more likely to be idle.

Now we follow the same reasoning that we used in the example presented in the Introduction. Consider three individuals $\{i, j, k\}$ with $x_i < x_k < x_j$.¹⁹ The probability that i and j meet is weakly higher than the probability that k and j meet because $\mu'(x_i) \ge \mu'(x_k)$ (so that, at any particular point in time, i is more likely to be idle than k). On the other hand, the probability that each of these match upon meeting is the same. Indeed, this probability is 1 - F(v(j)) which is the probability that j accepts the match. Thus, (i, j) is the most likely to form. The comparison between (i, j) and (i, k) is a bit more complicated because they differ along both dimensions. On the one hand, j is less demanding than k because her name is less likely to be ranked first in a random match. On the other hand, j is the less likely to be unmatched than j). Nevertheless, we show in the Appendix that this is a second-order effect and (i, j) is also the most likely match among all matches including i. This establishes negative correlation because (i, j) is more likely that (i, k) or (k, j).

Proposition 2. The distribution of names under the alphabetical rule exhibits negative correlation.

Furthermore, the alphabetical rule will also have consequences in terms of realized output. We define a match (i, j) to be efficient if there exists $\eta \in (0, 1)$, such that $\eta y \ge v(x_i)$ and $(1-\eta)y \ge v(x_j)$. Notice that in an efficient allocation matches are formed if and only if they are efficient. This is the case if $\alpha = \frac{1}{2}$ since in such a case $v(x) = v^*$. If

¹⁹Following the example in the Introduction, one may think of i as Mr. Dundee, k as Ms. Espinoza, and j as Ms. Yeats.

 $\alpha \neq \frac{1}{2}$ and authors cannot commit to side-transfers, however, there are efficient matches that will not be formed in equilibrium because the second author may not receive enough surplus from the match so as to compensate her to accept it even if the first author would get a surplus. In particular, if $\frac{\alpha}{1-\alpha} > \frac{v(x_i)}{v(x_j)}$, there exists values of $y \ge v(x_i) + v(x_j)$ for which the match is not formed.

4 Mapping the Model to the Data

One crucial assumption of the model is that there is random matching among idle individuals. That is, we have assumed that the probability that i and j meet equals $\mu'(i)\mu'(j)$. This assumption, however, may be violated for many reasons. For instance, it may be the case that some people are more likely to meet with others with whom they share a mother tongue. If different languages have different distributions of names, then the probability that i and j meet may not equal the product of their frequencies in the overall population. Therefore, we need a counterfactual distribution of names with which to compare the resulting distribution under the alphabetical rule. We tackle this issue using the distribution of names in articles that do not respect the alphabetical order. While most articles respect the alphabetical order, approximately 15% of the articles do not (see Table 3).

We call those articles *switchers*. Authors may decide to switch for many reasons. Some may decide the order in which the authors are listed at the end of the project (e.g. if an author is rewarded because she contributed more than the rest) but others would decide it at the moment of forming a match. For instance, authors may decide to switch because they differ in seniority or prominence in the profession, because one of the authors had access to a unique data set or some essential funding, or because one of the authors had the initial idea and looked for collaborators to join the project. In any of these cases, it is reasonable to assume that the incentives to match based on names, as described in our theoretical model, do not apply (or, at any rate, apply to a lesser degree). If the original distribution of names of *switchers* and *non-switchers* were identical but the distribution of *realised matches* in each group differs (in the direction predicted by the model) we can conclude that the alphabetical rule encourages some strategic matching. Hence, we have the following exclusion restriction.

Condition 3. The propensity of an individual to become a switcher is uncorrelated with the distribution of her potential matches.

In essence, this assumption requires that the individual propensity of an individual to switch does not vary systematically across communities (e.g. languages).²⁰ Since names do

 $^{^{20}}$ Of course, this assumption only needs to be valid for individuals in our sample. See Subsection 5.4 for a discussion.

not affect payoffs for switchers, the distribution of realized matches should then be equal to the distribution of potential matches. We shall test for difference in the distributions of names across matches in both groups. In the simple case of two-authored papers, this can be performed with a simple test in which we compare the average of the absolute value of the difference between the name indices of authors in both tests. This formulation has the advantage that it is easy to extend to articles with three or more authors and also provides an estimate that is easy to interpret. Notice that under independence, the average distance is 1/3, and the average distance can take any value between 0 and $\frac{1}{2}$.²¹

The estimated difference can be thought of as an Average Treatment Effect, where the treatment is to be subject to the alphabetical rule. Unfortunately, we only observe the treatment status imperfectly, leading to a downward bias in the estimated coefficient but preserving identification. The reasons for this are threefold. First, we categorize all articles that respect the alphabetical order as *non-switchers*, but undoubtedly some of them followed a different convention that turned out to deliver the same ranking as the alphabetical order.²² Second, insofar as some switchers only decided the ranking after completion, their matching strategies may not have differed from that of non-switchers. Finally, our codification of (compound) last names may not fully agree with the codification used by the authors.

Notice also that the model predicts that individuals whose name comes later in the alphabet are more likely to accept a match, and, therefore, are more prolific. From Van Praag and Van Praag (2008) we know that this prediction is not borne out by the data. If we maintain the assumption that names are uncorrelated with ability, this discrepancy may arise because first-authors become more *visible* and visibility may translate into higher likelihood of being part of future matches. For instance, if better-known authors are more likely to meet other coauthors, or if they are more likely to get feedback and get to disseminate their work faster, they may get to produce more papers even if they are *pickier*. Since the correlation stems from different degrees of pickiness, our testable implications would remain true in a more general model that included such features.

5 Empirical Results

Our theory predicts that the average distance in alphabetical rank between pairs of coauthors will be larger for papers whose authors are listed in alphabetical order as compared with papers whose authors are not. Therefore, a statistic in which we have primary interest is the difference between the distances in alphabetical rank of co-author pairs across these two groups. We are able to compare the means across these two groups using a t-test

²¹See the Appendix for a proof of this statement

²²Indeed, only half of the two-author articles that used a non-alphabetical rule will be categorized as switchers.

due to the central limit theorem (given the sample size of each group) and because we assume that the alphabetical distances between co-authors who switch and who do not switch are independent from one another. That is, it is reasonable to assume that the alphabetical distance between two co-authors in the non-switcher group should not imply anything regarding the alphabetical distance between co-authors in the switcher group, and vice-versa. The only instance we can conceive which would violate this assumption is if the same co-author pair appears in both samples. In our data, 1,361 of the 42,193 co-author pairs appear as both non-switchers and switchers, and our results will be shown to be robust to removing all 4,334 of these associated papers from the analysis.

Along these lines, Table 5 reports the differences between the distances in alphabetical rank across non-switchers and switchers overall as well as within various subgroups of co-author pairs. Overall, the average distance between non-switchers is approximately 0.01 (3%) larger than for non-switchers. This difference in distances is statistically significant at the 1% level, as can be seen in the first row of Table 5. That is, co-authors who conform to the alphabetical norm are located further away from each other in the alphabet relative to co-authors who do not conform to the alphabetical norm. The magnitude of the difference across both groups is also relevant from an economic perspective. A simple calibration exercise with the model presented in Section 3 reveals that the implied value of α (i.e. the share in the proceedings that goes to the first author) is close to 0.6 and the probability that a match is formed drops by 10%.²³ Using an implied value of $\alpha = 0.6$, in Figure 1 we simulate the cumulative distributions of co-author alphabetical distances for non-switchers. Note the similarity between the simulated distributions and the actual cumulative distribution functions of alphabetical distances between co-authors, as shown in Figure 2.

Notice also that we would not have been able to identify the effect without using the sample of switching articles as a control group because the average distance of non-switchers is not different from 1/3. This is the product of the confounding factor of non-random matching and highlights the difficulties of studying the outcomes of a matching process in a natural environment.

We now explore the robustness of this finding across different sub-samples.

5.1 Sub-sample Analysis

5.1.1 Eras

Academics and the economics profession in particular have certainly evolved over the last several decades. One primary facilitating factor of increased collaboration has been the

²³Note that one might claim that multiple instances of the same co-author pair should only be counted once due to the fact that any meetings following the initial meetings cannot be considered to be random. A mean comparison across switchers and non-switchers in which we only count a given co-author pair once (within the category of switchers or non-switchers) has no effect on our results.

advent of the Internet. Therefore, and to the extent that a sufficiently large selection of potential co-authors may be required in order for strategic issues to play a role, we might expect for our finding to be stronger for more recent papers. On the other hand, however, as information technologies have improved, the economics discipline has also featured more empirical work. Insofar as these tasks may require a larger number of collaborators, the ratio of opportunities to co-author to the number of potential collaborators may not have changed significantly. As can be seen in Table 5, we do indeed find that non-switchers are more negatively correlated with one another than switchers in both the pre-Internet and post-Internet era.²⁴

5.1.2 Journal Ranking

It might also be the case that individuals choose co-authors more strategically when working on projects which they think are destined for the most highly ranked journals because such articles are more likely to receive a high number of citations. Therefore, it may be that the effect that we predict will be stronger at the most highly ranked journals. For this purpose we single out a small sub-sample of 22 (out of 91) journals we observe. We refer to this group of journals as Journal Group I. This group includes the well-known Top 5 journals in economics, nine additional top-tier general interest journals, as well as eight top-tier field journals. The difference across non-switchers and switchers in this group is in the expected direction and highly significant. In contrast, the p-value associated with the difference between non-switchers and switchers in Group II is only .106 despite the fact that these articles comprise approximately 62% of the sample. Examining the Top 5 journals only, the difference is in the expected direction but the p-value associated with this difference is 0.08. Since articles from these five journals only constitute approximately 12% of the sample, this subgroup may suffer from a relatively small sample size.

5.1.3 Alphabetical rank

The effect of rank in the alphabet on the difference in co-author alphabetical distance across non-switchers and switchers is not immediately obvious. If co-authors randomly matched, then it is easy to show that the average distance of co-authors is quadratic in alphabetical rank. That is, the average distance decreases at a decreasing rate until it reaches a minimum at the median name rank of the alphabet, after which it increases at an increasing rate. However, if co-authors match according to our theory, this relationship is somewhat more complex. A simulation of the model suggests that the discrepancy in alphabetical rank between co-authors across non-switchers and switchers is likely to be larger at the beginning of the alphabet because it is hardest for authors at the beginning

²⁴Likewise, we do not find any difference in the comparison between switchers and non-switchers when the sample is split approximately into half according to article length. The data indicate that articles have become longer over time.

of the alphabet to match. This is due to the fact that these authors have the highest reservation idea quality values. However, when allowing for a quadratic relationship between alphabetical rank and alphabetical distance from one's co-author (see Figure 3), we only find a significant difference (in the expected direction) in the middle of the alphabet.

5.2 Regression Framework

We also examine the difference in distances of co-authors across non-switchers and switchers using OLS and display the results in Table 6. Specification (2) indicates that the statistical difference between non-switchers and switchers is similar in different eras, and specification (3) echoes the finding from Table 5 that the difference in strategic behavior across non-switchers and switchers is more prominent amongst journals which we classify in Journal Group I. Specification (4) is easier to interpret in graphical form, as discussed above and displayed in Figure 3.

5.3 Papers with three authors

The principle behind co-author matching pairs should extend to triplets of co-authors as well. However, the phenomenon of three-author papers has only become widespread in the last two decades, and therefore the sample with which we may analyze such papers is about one-third in size relative to our sample of co-author pairs. In addition, the way in which three co-authors match is undoubtedly more complex than the way in which a pair of co-authors match. Furthermore, while there is only one way in which two authors may switch alphabetical order, there are six ways in which one may list three authors. These considerations imply that providing compelling evidence of strategic behavior in three-author papers is quite challenging. Our goal, therefore, is to provide some evidence that the difference in distributions we established for two-authored papers may also be found in the three-author case.

First, given that there are six ways in which one may list three authors, the definition of switching is not as obvious in three-author papers as it is in two-author papers. Given the relative prominence of the first author in any paper with multiple authors, and given that three author papers are often cited using the first author's name followed by *et al.*, a switch in alphabetical order between the second and third co-authors in alphabetical rank would not seem to be as important for purposes of how each author is recognized as a switch in alphabetical order between the highest alphabetically-ranked author and either of the two other authors. Therefore, we define a switch in a three-author paper as an instance in which the alphabetically highest-ranked author is not listed first.

If three co-authors are matched randomly in a uniform distribution of authors, the average distance between the first and second co-author will be 0.25 whereas the average

distance between the first and third co-author will be 0.5. As noted above, since we only consider a switch to be an instance in which the highest ranked author is not listed first, we are less interested (and indeed are not well-informed) with regards to strategic behavior between the second and third co-authors.

We can therefore extend the two-author paper mean comparison test by simply adding the absolute value of the difference between the alphabetically highest ranked author and the second highest alphabetically ranked author with the absolute value of the difference between the alphabetically highest ranked author and the lowest alphabetically ranked author. The results, which are generally consistent with our results in the two-author papers, are displayed in Table 7. We also analyze alphabetical distance between co-authors across switchers and non-switchers in three-author papers in a regression framework and display the results in Table 8.

5.4 Co-authors with the same last name

As noted earlier, there is ample evidence that most of 592 co-author pairs which share the same last name belong to the same family. While "industry knowledge" would support this claim, it is reinforced by the fact that randomly matching first and second co-authors in our sample yields only 10 matches with the exact same last name. Obviously, classifying all such pairs as *non-switchers* would result in positive bias of alphabetical rank correlation amongst non-switchers due to the nature in which co-authors both meet and match. Instead, we re-rank all individuals using both first and last names and perform the analysis. Only 427 among those 592 articles respect the alphabetical order once we take into account first names, suggesting that the alphabetical norm is less prominent for first authors. As a result, the difference in means across groups is even larger, as reported in Table 9. Notice, in particular, that differences are statistically significant in all sub-samples.

5.5 Understanding switching

As noted earlier, one may think of several possible reasons for why co-authors would violate the alphabetical norm. In order to disentangle them, we use a simple regression framework where we estimate the probability of switching based on different observable characteristics of the authors. Results are reported in Table 10. Perhaps surprisingly, we find no evidence for the hypothesis that switching occurs in order to increase visibility by listing first more senior authors. If anything, articles in which the difference in the academic age of authors (as measured by the difference in years since the first publication) is larger are less likely to violate the alphabetical norm. On the other hand, we do find some evidence that switching is more likely for less valuable articles. Indeed, it is significantly more likely that authors switch in a short paper published in a second-tier journal as compared with a long article in a first-tier journal. In any case, the explanatory power of our analysis is very small. 25

The most relevant question for our purpose is whether a violation of the alphabetical norm is correlated with two co-authors' distance from one another in the alphabet. That is, are two co-authors who are closely ranked to each other in the alphabet more likely to violate the norm than two co-authors are more distantly ranked from one another? In the absence of a reason for co-author rank distance to influence the decision to violate the norm, a co-author pair's reason for switching should not bias our results.

We are aware of circumstances in academics in which this indeed may be the case. For example, we have some anecdotal evidence that Chinese universities tend to weight the contribution of the first-listed author more heavily than any subsequent author when rewarding research output. Given that Chinese names, as written using the Pinyin transcription to the Latin alphabet, are distributed differently than Western names, the distribution of potential co-authors of switchers may differ from that of non-switchers. While this may be an important concern for recent articles or articles in second-tier journals, our results are strongest for older papers in top-tier journals, suggesting that this is not the driving force behind the disparity of mean absolute differences.²⁶

6 Conclusion

In this paper we have provided evidence of distortions in the distribution of matches across co-authors in the field of economics. Our evidence is consistent with strategic behavior in a framework where credit is awarded based on some exogenous characteristic (alphabetical order). Our simple theoretical framework delivers clear empirical predictions regarding the distribution of names in papers depending on whether they respect the alphabetical rule or not, and these predictions are verified by the data.

In light of these results, one may wonder whether the alphabetical norm is suboptimal. Our answer to that question is, however, nuanced. First, our theoretical framework abstracts from important issues like effort provision by co-authors and haggling costs that would accrue if the order should be bargained upon before agreeing upon a match. A simple social norm also helps to anchor expectations (Maciejovsky, Budescu, and Ariely (2009)) and, therefore, alleviates frictions in the market at large. Nevertheless, the alphabetical norm is by no means the norm in academics more generally. As economics becomes

 $^{^{25}}$ There are also 1,361 (out of 42,193) co-author pairs in our data which alternate in alphabetical order across articles. Even after their removal, non-switching co-authors are statistically significantly more distant from one another in the alphabet than switching co-authors by a factor similar to that reported in our empirical results.

²⁶Unfortunately, we do not have reliable affiliation data for most of the authors in the sample. More importantly, a direct test built by omitting names from a given language in our sample would produce bias estimates, because the resulting distribution of names would not coincide with the distribution of potential matches.

a more collaborative and experimental discipline and, therefore, asymmetric task distribution becomes more prominent, it would seem reasonable to reconsider the status of the norm.

More generally, our work sheds light on the effects of reward schemes on the matching of individual agents in teams. We have shown that the effects of an uneven distribution based on an unambiguously payoff-irrelevant variable has substantial effects on the efficiency of the market. While such schemes are rare, seniority or gender-based rewards are commonplace. Insofar as these characteristics have a higher impact on the distribution of rewards as compared with the creation of value, our results are likely to apply.

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A Omitted Proofs

Proof of Lemma 1. We first prove that there exists an equilibrium in which U(x) is decreasing in x. That is, for every x_i and x_j such that $x_i < x_j$, $U(x_i) \ge U(x_j)$. To see this, consider the possible matches that a given individual can establish as a function of her type. Let x_k be the name of the individual with whom she matches. If $x_k < x_i$, both would be second-authors, so that x_i can mimic x_j and accept whenever x_j accepts, yielding the same payoff. If $x_k > x_j$, both x_i and x_j will accept the match if x_k accepts so that they obtain the same payoff. Lastly, if x_k rejects both offers, both x_i and x_j receive the same payoff. Hence, we only need to consider what happens if $x_i < x_k < x_j$. Clearly, if x_k accepts a match with x_i , x_i receives a higher payoff that x_j could obtain. If, on the other hand, x_k rejects a match with x_i but x_j accepts a match with x_k , it must be that $U(x_k) > U(x_j)$. Hence, in equilibrium values are non-decreasing. Now assume that there exists a region in which $U(x_i) < U(x_i)$. By the preceding argument this requires that x_k rejects a match with x_i but x_j accepts a match with x_k for some non-degenerate set $X_k \subset (x_i, x_j)$. Hence, for all such x_k , it must be that $U(x_k) > U(x_j)$. Now take $x^* = \inf_x X_k$. Clearly $U(x^*) > U(x_i) > U(x_i)$. But by construction there is no $x_l \in (x_i, x^*)$ with $U(x_k) > U(x^*)$ so that if x_l rejects a match with x_i , then x^* will reject a match with x_l . This is a contradiction with $U(x_i) < U(x_l)$.

Now notice that for both x = 0 and x = 1, the name of their matches is irrelevant. Clearly, x = 1 could simply mimic x = 0 and guarantee herself $U(1) \ge U(0)\frac{1-\alpha}{\alpha}$. Since U(x) is non-decreasing, this guarantees that the second type will always come from the lowest-ranked name. Hence, the payoff of x = 0 only depends on the strategies of those individuals with whom she matches.

Proof of Proposition 2. It remains to be shown that, if $x_i < x_j < x_k$, then (i, j) is less likely than (j, k). To establish that, notice that

$$\Pr(ij) = (1 - F(v(x_j)))\mu'(x_j)$$
(5)

In order to save notation let $1 - F(v(x_j)) = q_j$. Using the Definition of $\mu'(x)$ we have

$$\Pr(ij) = \frac{\lambda q_j}{\mu(x_j)q_j + \int_{x_j}^1 q_l d\mu(x_l) + \lambda}$$
(6)

Hence,

$$\frac{\Pr(ij)}{\Pr(ik)} = \frac{q_j(\mu(x_k)q_k + \int_{x_k}^1 q_l d\mu(x_l) + \lambda)}{q_k(\mu(x_j)q_j + \int_{x_j}^1 q_l d\mu(x_l) + \lambda)}$$

Since q is non-decreasing, $\int_{x_j}^1 q_l d\mu(x_l) \ge (\mu(x_k) - \mu(x_j))q_j + \int_{x_k}^1 q_l d\mu(x_l)$. Substituting this

condition and substituting yields

$$\frac{\Pr(ij)}{\Pr(ik)} \le \frac{q_j(\mu(x_k)q_k + \int_{x_k}^1 q_l d\mu(x_l) + \lambda)}{q_k(\mu(x_k)q_j + \int_{x_j}^1 q_l d\mu(x_l) + \lambda)} \le 1$$

Lemma 4. The average distance of co-authors d(x, y) satisfies $0 \le d(x, y) \le \frac{1}{2}$.

Proof. Let y(x) be the matching function. The first bound is trivially tight since for every $\xi > 0$ we can take $y(x) = x + \frac{1}{2}\xi$ yielding the result. The second bound is also tight since y(x) = 1 - x if $x \in [0, \frac{1}{2}]$ and $y(x) = \emptyset$ otherwise yields $d(x, y(x)) = \frac{1}{2}$. To see that it is indeed an upper bound, notice first that the image of y(x) will never overlap with its range for otherwise there is a pair (x, y(x)) and another pair (x, y(x')) such that x' > y(x). But then swapping to a pair of matches (x, x') and (y(x), y(x')) would increase the distance. But then, the problem is to find a function y(x) to maximize

$$\int |y(x) - x| dx = \int_{Y} y dy - \int_{X} x dx$$
(7)

since y(x) > x. So all matches satisfying this condition yield the same expected distance: namely 1/2.

B Alternative Models

We now explore an alternative model of scientific collaboration for purposes of comparison.

Idea-Holders and Collaborators

We have assumed that all ideas are generated upon matching and cannot be transferred across matches. It may be, however, that the idea is held by one of the authors, who can then decide to preserve it for future matches. In this scenario, only one of the two individuals in a potential match acts strategically (the idea-holder), in contrast to the model in the paper, whereby both individuals act strategically.

The matching process is as follows. At the beginning of a period an idea-holder is matched with a set of potential collaborators. The idea-holder proposes to (at most) one of them. If the chosen collaborator accepts, the article is completed. Otherwise, the idea-holder moves on to the next period, preserving her idea and facing a new set of potential collaborators. For simplicity, we assume that all ideas are equally good and the probability of having an idea in a given period is small (ideas are scarce). We now describe the equilibrium of the model.²⁷ If a collaborator receives an offer from a co-author ranked below her, she accepts it (if she receives more than one offer, she just chooses one at random). Otherwise, she accepts one of the offers to be the second co-author. Given this policy, due to the scarcity of ideas, it is optimal for idea-holders to offer co-authorship to authors ranked below them in the alphabet, if there are any (if ideas are not scarce then the model becomes substantially more complex). If there is more than one potential coauthor, then there exists a cutoff x_1 such that if the name of the lowest-ranked potential collaborator ranked below the idea-holder is $x < x_1$, then the idea-holder should choose that one. Otherwise, she randomizes among those above her, with higher probability placed on higher-ranked authors. The randomization ensures that all of them give her the same expected payoff. If all collaborators are ranked above, then if the name of the idea-holder is low enough, the idea-holder waits one more period. Otherwise, she offers first-authorship to one of the collaborators, chosen at random according to an increasing distribution function. Notice that, contrary to the model presented in the main text, in this setup, the probability that two random individuals match is decreasing in the distance between their names. Indeed, if the idea-holder finds a co-author with a name ranked below her, she will offer co-authorship with higher likelihood to those ranked higher (i.e. closer to her). If she only finds a co-author ranked above her, either she waits one more period or she chooses one at random. In this latter case, she chooses those closer to her with higher probability.

 $^{^{27}\}mathrm{Details}$ are available upon request

C Tables

		Reservation idea quality			
Author	Alphabetical rank	As second co-author	As first co-author		
Dundee	1	14	7		
Espinoza	2	12	6		
Yeats	3	10	5		
Yu	4	8	4		

Table 1: A simple four-author world

Table 2: Simple co-author matching example

	Match $\#1$	Match $\#2$	Match $\#3$
Co-author pair $\#1$ Alphabetical distance	Dundee-Espinoza 1	Dundee-Yeats 2	Dundee-Yu 3
Minimum idea quality	12	10	8
Co-author pair $\#2$	Yeats-Yu	Espinoza-Yu	Espinoza-Yeats
Alphabetical distance	1	2	1
Minimum idea quality	8	8	10
Average alphabetical distance	1	2	2

Table 3: Data

	Number of Articles	Switches	Exact Matches
1 Author	$98,\!250$	NA	NA
2 Authors	$60,\!648$	10,091	595
3 Authors	22,742	$5,\!571$	155
4+ Authors	1,105	560	NA

Table 4:	Number	of ob	servations	bv	iournal
				· •/ •)

Journal Group I	Total	Journal Group II	Total
American Economic Review	3,045	American Journal of Agricultural Economics	889
Econometrica	1,178	Applied Economics	1,800
Economic Journal	1,150	Brookings Papers on Economic Activity	161
European Economic Review	1,243	Canadian Journal of Economics	881
Games and Economic Behavior	777	Ecological Economics	1,141
International Economic Review	890	Economic Development and Cultural Change	522
Journal of Business & Economic Statistics	670	Economic Inquiry	247
Journal of Development Economics	945	Economic Policy	118
Journal of Econometrics	$1,\!454$	Economic Theory	798
Journal of Economic Literature	161	Economica	529
Journal of Economic Perspectives	390	Economics of Education Review	565
Journal of Economic Theory	1,332	Empirical Economics	611
Journal of Financial Economics	913	Environmental & Resource Economics	560
Journal of Labor Economics	372	Experimental Economics	133
Journal of Monetary Economics	848	Explorations in Economic History	294
Journal of Political Economy	1,072	Health Economics	495
Journal of Public Economics	1,372	International Journal of Game Theory	288
Journal of the European Economic Association	225	International Journal of Industrial Organization	626
RAND Journal of Economics	566	International Tax and Public Finance	290
The Review of Economics and Statistics	$1,\!540$	Journal of Accounting and Economics	574
Review of Economic Studies	790	Journal of Banking & Finance	$1,\!624$
The Quarterly Journal of Economics	759	Journal of Comparative Economics	440
		Journal of Development Studies	788

Journal of Economic Behavior & Organization

Journal of Economics & Management Strategy

Journal of Financial and Quantitative Analysis

Journal of Law, Economics and Organization Journal of Mathematical Economics

Journal of Institutional and Theoretical Economics

Journal of the Japanese and International Economies

Journal of Environmental Economics and Management

Journal of Economic Dynamics and Control

Journal of Economic Growth

Journal of Health Economics

Journal of Human Resources

Journal of Industrial Economics

Journal of Law and Economics

Journal of Population Economics

Journal of Regulatory Economics Journal of Risk and Uncertainty

Journal of Urban Economics

Macroeconomic Dynamics

Oxford Economic Papers

NBER Macroeconomics Annual

Review of Economic Dynamics

Review of Industrial Organization

Scandinavian Journal of Economics

The Journal of Economic History

World Bank Economic Review

World Bank Research Observer

Scottish Journal of Political Economy

The Journal of Real Estate Finance and Economics

Review of Income and Wealth

Weltwirtschaftliches Archiv

Social Choice and Welfare

The Energy Journal

The World Economy

World Development

Southern Economic Journal

Oxford Review of Economic Policy

Regional Science and Urban Economics

Oxford Bulletin of Economics and Statistics

Mathematical Finance

National Tax Journal

Labour Economics

Land Economics

Public Choice

Journal of International Economics

Journal of Money, Credit and Banking

1,063

1,030

 $\frac{91}{309}$

646

817

605

591

431

206

860

403

 $\begin{array}{c} 203 \\ 605 \end{array}$

32

371

 $\begin{array}{c} 310\\ 266 \end{array}$

272

676

397

768

321

167

399

8

545

524

276

1,188

638

262

359

250

430

478

402

405

363

342

512

431

573

201

108

1,490

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	Non-switchers	Switchers		Difference
Overall Standard Deviation Obs.	$\begin{array}{c} 0.332 \\ (0.236) \\ 48,081 \end{array}$	$\begin{array}{c} 0.323 \\ (0.235) \\ 9,609 \end{array}$	Standard Error Obs.	$\begin{array}{c} 0.008^{***} \\ (0.003) \\ 57,690 \end{array}$
Before 1995	$0.33 \\ (0.234) \\ 14,501$	$\begin{array}{c} 0.319 \\ (0.233) \\ 3,282 \end{array}$		$\begin{array}{c} 0.012^{**} \\ (0.005) \\ 17,783 \end{array}$
Since 1995	$\begin{array}{c} 0.332 \\ (0.237) \\ 33,580 \end{array}$	$\begin{array}{c} 0.326 \\ (0.236) \\ 6,327 \end{array}$		0.006^{**} (0.003) 39,907
Journal Group I	$\begin{array}{c} 0.332 \\ (0.235) \\ 19,190 \end{array}$	$0.314 \\ (0.231) \\ 2,502$		$\begin{array}{c} 0.017^{***} \\ (0.005) \\ 21,692 \end{array}$
Journal Group II	$\begin{array}{c} 0.332 \\ (0.237) \\ 28,891 \end{array}$	$\begin{array}{c} 0.327 \\ (0.236) \\ 7,107 \end{array}$		$\begin{array}{c} 0.005 \ (0.003) \ 35,998 \end{array}$
Top Five	$\begin{array}{c} 0.333 \\ (0.234) \\ 5,968 \end{array}$	$0.319 \\ (0.238) \\ 876$		0.015^{*} (0.008) 6,844
Short articles	$\begin{array}{c} 0.332 \\ (0.237) \\ 23,790 \end{array}$	$\begin{array}{c} 0.323 \\ (0.231) \\ 3,667 \end{array}$		0.009^{**} (0.004) 27,457
Long articles	$\begin{array}{c} 0.331 \\ (0.236) \\ 23,182 \end{array}$	$\begin{array}{c} 0.323 \\ (0.237) \\ 5,634 \end{array}$		0.009^{**} (0.004) 28,816

Table 5: Differences in means: Non-switchers vs. switchers

Note: The null hypothesis that the difference between non-switchers and switchers is equal to zero. The alternative hypothesis is a two-sided test that the difference is not equal to zero.

Table 6: OLS analysis of two-author papers

Dep Var: Absolute difference in alphabetical rank

Switch	(1) - 0.008^{***} (0.003)	(2) - 0.012^{**} (0.005)	$(3) \\ 0.005 \\ (0.004)$	$(4) \\ 0.014 \\ (0.009)$
Since 1995		$0.002 \\ (0.003)$		
Journal Group I			-0.000 (0.003)	
Short article				
Since 1995 x Switch		$0.005 \\ (0.006)$		
Journal Group I x Switch			-0.012^{*} (0.006)	
Author rank				-0.964^{***} (0.019)
Author rank squared				$\begin{array}{c} 0.967^{***} \\ (0.019) \end{array}$
Author rank x Switch				0.082^{**} (0.038)
Author rank squared x Switch				0.064^{*} (0.037)
Constant	$\begin{array}{c} 0.332^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.330^{***} \\ (0.003) \end{array}$	$\begin{array}{c} 0.332^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.491^{***} \\ (0.004) \end{array}$
Ν	$57,\!690$	57,690	57,690	115,380

Note: Regressions which include author rank count each paper twice - once utilizing the first author's rank and once utilizing the second author's rank. Standard errors are clustered by co-author pair and therefore standard errors are unaffected by double counting each paper.

Table 7: Mean comparisons in three-author papers

Overall S.D. Obs.	Non-switchers 0.743 (0.375) 15,871	Switchers 0.728 (0.370) 5,097	S.E. Total Obs.	Difference 0.015** (0.006) 20,968
Before 1995	$\begin{array}{c} 0.745 \\ (0.395) \\ 2,555 \end{array}$	$\begin{array}{c} 0.735 \\ (0.365) \\ 928 \end{array}$		$0.010 \\ (0.015) \\ 3,483$
Since 1995	$\begin{array}{c} 0.743 \\ (0.371) \\ 13,316 \end{array}$	$\begin{array}{c} 0.727 \\ (0.372) \\ 4,169 \end{array}$		0.016^{**} (0.007) 17,485
Journal Group I	$\begin{array}{c} 0.734 \\ (0.368) \\ 5,805 \end{array}$	$\begin{array}{c} 0.717 \\ (0.370) \\ 1,044 \end{array}$		$\begin{array}{c} 0.017 \\ (0.012) \\ 6,849 \end{array}$
Journal Group II	$0.749 \\ (0.378) \\ 10,066$	$0.731 \\ (0.370) \\ 4,053$		0.018^{**} (0.007) 14,119

Sum of both co-author pairs

Note: For three-author papers, we define switching as an instance in which the author with the highest alphabetical rank is not the first-listed author. The null hypothesis that the difference between non-switchers and switchers is equal to zero. The alternative hypothesis is a two-sided test that the difference is not equal to zero.

	Sum of h	both co-aut	hor pairs
Switch	-0.015^{*} (0.008)	-0.010 (0.026)	-0.017^{*} (0.011)
Since 1995		-0.002 (0.021)	
Since 1995 * Switch		-0.007 (0.025)	
Journal Group 1			-0.015 (0.010)
Journal Group 1 * Switch			$\begin{array}{c} 0.000 \\ (0.017) \end{array}$
Constant	$\begin{array}{c} 0.743^{***} \\ (0.006) \end{array}$	$\begin{array}{c} 0.745^{***} \\ (0.022) \end{array}$	0.749^{***} (0.008)
Ν	20,968	20,968	20,968

Table 8: OLS analysis of three-author papers

Note: Standard-errors are clustered by co-author triplet.

Table 9: Mean comparison in two-author papers when ranking authors using both first and last name (includes co-authors with the same last name)

	Non-switchers	Switchers		Difference
Overall	0.329	0.318		0.011***
S.D.	(0.237)	(0.237)	S.E.	(0.003)
Obs.	48,493	9,781	Total Obs.	58,274
Before 1995	0.327	0.313		0.014***
	(0.236)	(0.235)		(0.004)
	14,648	3,348		17,996
Since 1995	0.330	0.321		0.009***
	(0.238)	(0.238)		(0.003)
	33,845	6,433		40,278
Journal Group I	0.329	0.310		0.020***
-	(0.236)	(0.232)		(0.005)
	19,313	2,539		21,852
Journal Group II	0.329	0.321		0.008**
	(0.238)	(0.238)		(0.003)
	29,180	7,242		36,422

Note: There were eight observations in which both the first and last name of the co-author pair are identical; these articles were indexed by the data source incorrectly and should be listed as single-author papers and therefore are not included here. Two observations in which authors shared the same first and last name but different middle names (or initials) were classified as non-switchers.

Table 10: When do co-author pairs switch

	LPM		Logit par	Logit partial effects	
Seniority	-0.001***	-0.001***	-0.001***	-0.001***	
	(0.000)	(0.000)	(0.000)	(0.000)	
Since 1995		-0.032***		-0.032***	
		(0.004)		(0.004)	
Journal Group I		-0.085***		-0.091***	
		(0.003)		(0.006)	
Short article		0.056***		0.057***	
		(0.003)		(0.003)	
Constant		0.191***			
		(0.004)			
Ν		57,688		57,688	

Note: Seniority is defined as the difference in the year of the alphabetically higher-ranked author's first publication and the year of the alphabetically lower-ranked author's first publication. If seniority of the alphabetically lower-ranked author were to increase the likelihood of switching, then we would expect a positive coefficient. If seniority of the alphabetically lower-ranked author were to decrease the likelihood of switching, then we would expect a negative coefficient. Two observations are omitted due to absence of publication year data. Standard errors are clustered at the co-author pair level.

Figure 1: Simulated distributions of co-author match distances (assuming $\alpha = 0.6$)





Figure 2: Actual distributions of co-author match distances

Figure 3: Alphabetical distance by alphabetical rank: Non-switchers vs. switchers

