On the Causal Effect of Fame on Citations*

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Abstract

Papers published in finance and economics journals whose first authors are famous have more citations than papers whose second or third authors are famous. As a paper ages, its citation rate varies most with variation in the fame of the first author and less so with the fame of second and third authors. Author order is alphabetical so these patterns are unrelated to underlying quality. The magnitudes we find are large: a three-author paper written by the most prolific author in economics and his two research assistants would increase, on average, its percentile rank by 30 percentage points if the prolific author was first, rather than second or third. The effect is especially pronounced in three, rather than two, author papers, suggesting that burying a famous author in the "et al" reduces citations the most.

JEL Codes: G00, J00, J70, Z10

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1. Introduction

An author's fame is often measured by her citation counts. We show that citations do not simply measure fame – they are caused by it. That is, two identical papers, one written by a famous author team and one written by a little-known author team, will receive substantially different citations. This result was famously hypothesized by Merton (1968) and dubbed *The Matthew Effect*. A number of papers written over the last 15 years have hinted at its presence but, to our knowledge, this is the first study to show that the effect is large and pervasive.

To show this result, an ideal study would follow Bertrand and Mullainathan (2004) and the subsequent literature: run an experiment, submitting to journals papers with different authors that are otherwise identical and observing their publication success and citation rates over time. For obvious reasons, this experiment cannot be run.[1]

Instead, we test a joint hypothesis: (i) the first author in a list receives more attention than later authors, and (ii) an author's fame causes her to be cited. The first part of the hypothesis has been extensively studied and confirmed in prior research and is obvious on its face with three- or four-author papers, references to which often bury later authors with the term *et al*.[2] The joint test is therefore ultimately about whether there is a causal effect of fame on citations. We find that papers published in finance and economics journals whose first authors are highly cited will receive more citations than papers whose second or third authors are highly cited.[3] Because these authors are typically ordered alphabetically, this is strong evidence that fame causes citations.

We consider all publications from 1974 to 2017 in a set of 48 prominent journals and all citations to those publications listed in Web of Science. We define a paper's *citation percentile* as its percentile ranking by citations among all papers published in the same year within our set of journals. For example, consider Kamenica, Mullainathan, and Thaler (2011), entitled "Helping consumers know themselves," and published

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[1] Similar experiments have been run in the world of fiction. In 1975 and 1979, aspiring writer Chuck Ross sent incorrectly attributed books (or sample pages) of 1969 National Book Award winner *Steps* to eight publishers and was rejected by all. In 2007, David Lassman sent opening chapters and synopses of a number of Jane Austen books to 18 British publishers and was roundly rejected. One publisher was keen to the hoax.

[2] We discuss this research in more depth in Section 2.

[3] To be clear, we are not studying whether papers whose first authors' last names appear earlier in the alphabet are more highly cited. This result has been shown conclusively in the literature: it generally benefits a paper (and an author) to appear earlier in lists. We ask whether a paper receives more citations because its authors are famous, over and above any correlations that author fame may have with the quality of the paper. We use the quasi-random nature of alphabetical author ordering in finance and economics as a laboratory to study this question, which is not settled. It is true that our results provide yet more evidence that people pay attention to earlier items in a list, but that is not our objective.

in the *American Economic Review*. The paper had 14 Web of Science citations as of July 2017, placing it in the 57th percentile among all papers written in 2011.[4]

A paper's citation percentile is a measure of its prominence in the field, and an author's count of high citation percentile papers is a measure of her prominence. We define a paper as a *home run* if it is in the top 5% of papers published that year (equivalently, has a citation percentile above 95%). We define an author's *fame* as the count of her high citation percentile papers; the more home runs that an author writes, the more famous she is defined to be. We then regress each paper's citation percentile on the fame of its first author, the fame of its second author, and, for three-author papers, the fame of its third author.

The null hypothesis is that the coefficients are equal and positive. More famous authors will naturally write more highly cited papers, but it should not matter whether a more famous author is listed first, second, or third. The alternative "fame" hypothesis is that the coefficient on the first author will be larger than the others.

We find that the first coefficient is indeed larger – much larger. To get a sense of magnitudes, consider again Kamenica, Mullainathan, and Thaler (2011). As of July 2017, the three authors had 3, 11, and 23 home run publications, in that order. Suppose that the author order for this manuscript were reversed. If citations were measuring only the quality of the paper, then it would remain a 57th percentile paper. Instead, according to our estimates, it would have been a 68th percentile paper. It is easy to find examples that generate even larger changes.

The effect is largest when we most strictly define fame. That is, if we define a home run to be a top 10% manuscript, the effect shrinks. If we define a home run as top 25%, the effect shrinks again. Author order matters most when one of the authors writes very highly cited papers.

If we restrict attention to citations coming from our set of 48 journals, we can track citations to individual papers over time. For each year after a paper is published, we observe the fame of all authors in that year and regress the citation percentile of the paper on each author's fame as well as paper fixed effects. This allows us to hold constant the set of authors and the long-run average citation percentile of each paper and evaluate how its citation rate changes as each author's fame increases or decreases. As authors become more famous, their previously written papers are cited more. What is more surprising is that papers whose first authors become more famous see a significantly higher increase in citations relative to papers whose second or third authors become more famous.

[4] If this seems low, it is because Web of Science is a lagging citation indicator and the data were collected in 2017.

All of these results are robust to dropping papers by the most prolific authors from the sample and to measuring an author's fame and paper's citation level using contemporaneous or cumulative counts. In sum, author fame causes citations, and the magnitude is large.

There are several reasons to be interested in the causal effect of fame on citations, the most important being that citations are used as a (supposedly) objective measure of impact in the promotion and tenure decisions of academics. Our results place a lower bound on the extent to which fame magnifies a researcher's citation count and that lower bound is high. Academics can acquire fame in many ways other than producing exceptional research, for example by traveling more to conferences or seminars, taking on editorial responsibilities at a journal, or appearing regularly in mainstream media. Fame can also arise from bias. If some groups are disproportionately put into positions of prominence, those groups will also be disproportionately cited. Using citations as a measure of a researcher's impact may therefore inject substantial bias into promotion and tenure decisions.

In Section 2 we present a brief review of the literature and in Section 3 discuss the data. In Section 4.1 we present our baseline results establishing a causal effect of fame on citations. The remainder of Section 4 is devoted to showing that the results are robust to a variety of alternative methodologies. Additional robustness is provided in the Appendix. Section 5 analyzes whether the effects that we find are large enough to affect career outcomes.

2. Literature

The citation process in economics has garnered substantial attention over the last few years, especially as it relates to bias in the publication process. Sarsons *et al* (2021) study differential attribution given to women and men who co-author and Card *et al* (2020) study long-run citations for papers written by women and men that get the same internal evaluations at top journals. Both find bias against female scholars. Heckman and Moktan (2020) show evidence that tenure in economics is highly dependent on a scholar's publishing in the top-5 journals, even though long-run citation rates are as high of higher for papers published in several other journals. Surprisingly, given other work on the topic, Hamermesh (2018) finds little difference in citation rates for scholars with early versus late names, especially among junior faculty. These recent papers are concerned with how bias in citations and publications may affect academic careers. The results presented in this manuscript add to this literature.

Our study also connects to a number of bibliometric literatures, both within and outside economics. Most closely related to our work, Simcoe and Waguespack (2011) evaluate publication rates for submissions to the Internet Engineering Task Force (IETF). Publication rates of submissions co-authored by high-status individuals were 77% lower when the high-status author's name was buried in an *et al* in the email announcing the submission.

Our study has some important differences. Citation and publication practices in computer science and economics could substantially differ; for example, it is common in computer science for papers to be published in conference proceedings. Unlike most publications in finance and economics, they often do not go through full peer review. Perhaps more importantly, the process at the IETF is significantly different from the process of peer review. Submissions to the IETF are viewed and vetted by the interested public, not hand-selected specialist referees. Public reviewers might be less well-versed in the current literature and more likely to rely on known names when vetting papers than authors and referees, who purportedly understand the full breadth of their field.

There is substantial work relating to the effect of alphabetical order on academic success.[5] Einav and Yariv (2006) look at the patterns of academic prominence for individuals with different last names. They find that academics with late names are less prevalent at top economics departments among tenured versus untenured faculty. This is not the case for lower-ranked departments. Their finding does not hold in psychology, a field that does not assign author order alphabetically. They also find that authors with late names are less likely to be fellows of the Econometric Society. Along these lines, Efthyvoulou (2008) finds that faculty with earlier last names are more likely to be at top departments, to have their work downloaded, and to be cited. Van Praag and van Praag (2008) find that early name authors publish more papers in top economics journals.

There is strong evidence that people read lists from top to bottom, so items listed first are disproportionately visible. Arsenault and Larivière (2015) document that papers whose first authors have early last names receive more citations. Huang (2015) shows that scientific papers with earlier first authors are more cited, but papers with earlier second, third, etc., authors are not. The latter result suggests that an association between author ability and last name is unlikely to explain the primary result, though the difference in roles between a first author and other authors in a scientific publication are typically quite large. The effect is more

[5] Weber (2018) surveys the literature on alphabetical listing of authors on papers and its effects. The author summarizes the key facts which are: (1) alphabetical listing of authors gives an unfair advantage to authors with last name initials early on in the alphabet, and (2) researchers react strategically to this form of discrimination. The survey documents that first authors are likely to be given more credit for joint work, early surname authors are more likely to work at top departments, and are more likely to receive awards, early surname authors are more likely to have an advantage in publishing papers, and an advantage in downloads and abstract views. Researchers react strategically to this kind of discrimination. Authors with late last names work less in large teams than early surnames. Authors with late surnames are more likely to write papers on their best ideas alone, are more likely to disrespect the alphabetical norm, and are more likely to manipulate their names to move up in the alphabet.

pronounced for papers with more co-authors, suggesting a culling of lists that get too long though, again, scientific papers with more co-authors can differ substantially from those with fewer.[6]

Perhaps most cleanly, Feenberg, Ganguli, Gaulet, and Gruber (2017) show that among papers published at the top of the NBER weekly digest, which at the time listed papers according to the first author's last name, were more downloaded, viewed, and cited than those listed at the bottom. The NBER has adopted random ordering in response. Haque and Ginsparg (2009) find the same result in the ArXiv paper repository.

Ray and Robson (2018) provide an alternative to alphabetical ordering for improving on the situation in which one's name affects one's success in academia. This mechanism allows credible signaling of author contributions to a paper and can invade the current environment in which ordering is alphabetical.

We apply the alphabetical ordering of names in finance and economics differently, not to investigate how last names affect career outcomes, but to identify the effect of fame on citations. That is, while these papers show that alphabetical ordering matters, *we take that fact as given in order to show that fame matters as well*.

Our paper also relates to two recent studies following citations of papers whose authors become more famous. Azoulay, Stuart, and Wang (2014) and McCabe and Babutsidze (2020) consider authors who have won the Howard Hughes Medical Investigator Award and the Nobel Prize in economics, respectively, and follow citations of their papers before and after they win the award. In both cases, using matched samples, they find a substantial increase in citations post-award even though their papers were already well-known and well-cited pre-award. We follow the same approach in some of our tests, but at both a broader and a more granular level. We measure the fame of all authors, award winning or not, over time and measure citations to their papers as their fame rises and falls. It is perhaps not surprising that, in the extreme example of Nobel Prize winners, fame causes citations. It may be more surprising that it does so for more mundane examples.

All of this work is consistent with the idea that "people cite what they see." Recent work by Teplitskiy *et al* provides causal evidence of the effect of conference presentations on citations. They show that people who showed interest in viewing a conference presentation were 52% more likely to subsequently cite the paper being presented if they had no scheduling conflict during the conference. This may be an example of a mechanism by which famous names in an author list lead to increased citations.

[6] Aad *et al* (2015), for example, has 5,154 authors, and most of their roles were not similar to those of the principal investigators'.

3. Data

Our data include all papers published in the set of journals outlined in Table 1. Most journals appear in our dataset in 1974 though some appear later. Each journal's date of first appearance is listed in Table 1. The journal list is drawn from Brogaard, Engelberg, and Parsons (2014) and the data for each paper, including citations, were downloaded from Web of Science in July 2017.

Our baseline analysis is simple. An observation is a published paper that has either two or three authors. Most analyses are performed separately for those two groups. We construct three critical variables that are not in the original data.

We first calculate each paper's *citation percentile*. For each year in the data, we select all papers published in that year across all journals in the sample for that year and we rank those papers by citations as of July 2017. Each paper's percentile in that ranking is defined as its citation percentile. The dependent variable in our baseline specification is the citation percentile multiplied by 100 (Note: a 95th percentile paper's citation percentile is 95, not 0.95).

We use citation percentile as our measure of a paper's citations for three reasons. Any given paper is cited more as it ages, confounding a paper's citations and its age. The overall level of citations has also changed over time: the volume of papers has grown but more recent papers have had less time to be cited. Furthermore, citation percentile is uniform whereas raw citations are highly skewed. These last two facts are apparent in Figure 1, which plots the level of citations to papers at various percentiles among all papers published in each year since 1974. The overall level of citations to papers published each year increases until approximately the year 2000 and then begins to decline. This is true for papers in the 95th percentile of all papers published that year, as well as papers published in the 90th and 75th percentiles. The skew in citations is clear, as the median paper receives few citations while the top 5 percent receive hundreds.

We next define each paper to be a *home run* or not based on its citation percentile.[7] Depending on the regression, we may define a paper to be a home run if its citation percentile is ≥95, ≥90, ≥75, ≥50, or ≥0. This last category simply defines all papers to be home runs. We will perform many analyses for all five definitions of home run, but it will often be useful to take a stand on the proper definition. When we do, we will define a home run to have a citation percentile ≥95. The number of citations required for a paper to be a home run in each year is shown in Figure 1.

[7] The term is taken from Brogaard, Engelberg, and Van Wesep (2018).

We then calculate the number of home runs that each author has in the sample, not including the paper in question. Suppose that paper A is a home run, for example, and paper B is not, and suppose that both papers share an author. If the author's home run count associated with paper A were X, then her home run count associated with paper B would be X+1. If both or neither were home runs, then her home run count for both papers would be the same. This count, for each author of a paper, is defined as the author's *fame*. There are naturally many authors who have only one publication in our journal list, and we assign them a value of 0 for fame, as they have 0 other papers that may be cited.

Table 2 provides summary statistics for our measures of fame. Statistics are calculated separately for two- and three-author papers. The average number of papers written by the first author on a two-author paper is 15.09 and the average number written by the second author is 15.27. These are higher than for three-author papers which are, given the rise in co-authoring over the last few decades, written by younger scholars.[8]

Continuing to increasingly well-cited papers, the average number written drops. The average number of papers written by the first (second) author of a two-author paper in the top 5% of all papers published in its year is 1.33 (1.43).

For two- and three-author papers, and for all definitions of fame, the average publication rates for authors in different positions in the author order are similar. *This fact is critical.* We treat the author order as quasi-random so if later authors were consistently more or less famous, our identifying assumption would be suspect.

Of interest may be the authors with the most highly cited publications. Andrei Schleifer, who has been both a first and second author on two-author papers, has 64 publications in the top 5% of papers published in the same year. He was never first author on a three-author paper in the top 5%. The most prolific first author on a top-5% three-author paper is James Heckman.

4. Results

4.1 Baseline effects of author order on citation percentiles

Our research design is variants of the following baseline regression:

$$y_{ijt} = \alpha + \beta_1 \times Fame_{ijt1} + \beta_2 \times Fame_{ijt2} + \beta_3 \times Fame_{ijt3} + \gamma_{jt} + \epsilon_{ijt,} \qquad (1)$$

[8] A mean number of papers of 13-15 may appear large, especially for younger scholars. The median author has 7-9 papers. Given that these numbers include authors of all vintages, they may not be as high as they first appear.

where y_{ijt} is the citation percentile x 100 for paper i, published in journal j, in year t; $Fame_{ijtk}$ is the fame of the k^{th} author of paper i; γ_{jt} is a fixed effect for journal j published in year t, and ϵ_{ijt} is an error. [9]

We believe this to be the simplest design that can deliver causal claims regarding our research question. Each β should be positive if some authors tend to write more highly cited papers than others. We are not, therefore, interested in the null hypothesis that the true coefficients are zero. Instead, our null is that the correlation of author fame and citations does not depend on whether the author is first, second, or third. Therefore, we provide results of F-tests for restrictions that $\beta_1 = \beta_2$ and $\beta_1 = \beta_3$. If fame causes citations and if citers tend to notice earlier authors more, then our alternative hypothesis is that $\beta_1 > \beta_2 \geq \beta_3$. We are especially interested in the *et al effect*: the importance of the first author's fame should be especially pronounced, relative to later authors, when there are at least three authors of a paper. This is because later authors' names will often be replaced by the term *et al* when a paper is cited, making them less visible.

Before we present results, we offer a brief digression into why more variables are not included on the right-hand-side of Equation (1). Many variables are known to affect a paper's citation rate, including field, methodology, age, etc. We could add measures of these properties, but we do not. This is for two reasons. First, running the simplest possible specification that is also well identified has academic merit by limiting the effect of specification choice on measured outcomes. That is, we avoid the garden of forking paths and the resulting false positives associated with it.[10] Second, we expect that most variables that one could add to Equation (1) would be subsumed by author fame: if papers in empirical corporate finance are more cited than papers published in theoretical banking, this should be incorporated into the authors' fame measures.

In order not to ignore the objection entirely, but to be consistent through all analyses, we always include journal-year fixed effects that at least partly account for field, age, etc. In Section 4.4, we have a more granular paper-year specification with paper fixed effects. In this specification, paper attributes like topic and methodology are absorbed into a paper fixed effect. We also add further controls in Appendix 3 and do not find substantially different results from those we discuss here.

In Table 3, Panel A, we present estimates in which y_{ijt} is citation percentile x 100, and papers have two authors. Each regression uses a different definition of home run when generating the fame variable. In

[9] We force the author order to be alphabetical. That is, even if authors choose a non-alphabetical order in practice, we assume that they chose to list names alphabetically. We perform the same analysis using actual author order in Appendix 4 and results are not substantially different. This is effectively an intent to treat design, in which the treatment is alphabetical author ordering.

[10] The Garden of Forking Paths is a short story written by Borges in 1941 but the term has been adopted by statistician Andrew Gelman to describe the process of researchers making false discoveries by reporting a small subset of outcomes of many empirical specifications.

column (1), every paper is defined to be a home run, so we are simply comparing how each author's total publication count (except for the paper in question) correlates with her citations. Surprisingly, the first author's total publications matter substantially more and the difference is highly statistically significant: the p-value for the F-test of $\beta_1 = \beta_2$ is <0.001. To get a sense of the difference, suppose that the first author has 40 publications and the second 15. The paper in question, holding journal-year constant, would be expected to have a [(17.083×40 + 12.861×15) - (17.083×15 + 12.861×40)]/100 = 1.06 higher citation percentile than if the author order were reversed. This might not seem large, but recall that this is for two-author papers, and we are defining fame to simply be publication count. The second author is never buried in the *et al* when the paper is referenced and the authors may not write many highly cited papers.

As we move to columns (2), (3), (4), and (5), we raise the threshold for a paper to be defined as a home run and therefore reduce the number of home-run papers. The coefficients on first- and second-author fame increase monotonically as we define fame more strictly. This should not be surprising: authors whose papers X and Y are more highly cited will also tend to receive more citations for paper Z. In each column, the first author's fame is more important than the second author's fame, and the differences are always highly significant.

Consider the same author pair as before, but now the first author has 40 95th percentile papers and the second has 15 95th percentile papers. The paper in question, holding journal-year constant, would be expected to have a 3.97 higher citation percentile than if the author order were reversed. In this example, the author with 40 home runs is one of the most cited and prolific authors in the profession. The author with 15 will be very well known within the field. The additional citations if the more famous author is first are large, given that the only difference is which author is listed first.

Table 3, Panel B, displays results from the same analysis for three-author papers. The number of observations drops by more than half, as two-author papers are much more common in our sample. If fame causes citations then we would expect the first-author effect to rise, as the use of *et al*, which hides later authors, usually begins at three. We would also expect larger coefficient differences and larger standard errors. This is indeed what we see.

Beginning again with the case where fame is measured simply as the number of papers that a person has published, X=0, the effect of a first author's fame is approximately double that of a third author's. The differences in the coefficients are again highly significant, with p-values of the F-tests that they are equal less than 0.001. Returning to our example of authors of varying fame, consider three authors, now with 40, 20, and 10 papers. The additional citation percentile points if the most famous is first and the least famous is last, versus the opposite, is 1.92. This is not a large magnitude, but this is also a weak definition of fame.

As we increase the threshold for a paper to be considered a home run, coefficients once again monotonically increase, consistent with fame more closely matching how we think of it intuitively. In all cases, the coefficient for first-author fame exceeds those for second- and third-author fame. The differences between the coefficients on the second and third author are smaller, and not always statistically significant at standard levels, consistent with *et al* being a primary driver of the effect.

Focusing on the strictest definition of a home run, X=95, consider a hypothetical paper whose first, second, and third authors have 40, 20, and 10 home runs, respectively, and compare two possible author orderings: one in which authors are ordered most to least famous and one in which they are ordered least to most famous. The difference in this hypothetical paper's citation percentile would be 16.13 percentage points.

It is worth noting that the coefficients on first- and second-author fame in the sample of two author papers are statistically significantly different regardless of how we calculate fame. This means that not all of the effect of author order works through the *et al* effect, which is only associated with three or more author papers. It is not obvious why author order should matter when all authors are typically identified when a paper is cited. There is also suggestive evidence that the second author's fame is more important than the third author's fame for three author papers, though the differences are not generally statistically different. We attribute both facts, especially the first, to the well-known finding that earlier items in lists are more noticed. This appears to be true in this sample even when names are not buried in the *et al*.

Establishing these baseline results is effectively our objective in writing this manuscript. We tested a joint hypothesis: people pay more attention to earlier items in a list and authors' fame *causes* citations, over and above any correlation between authors' fame and the quality of their papers. The first part of this joint hypothesis is by now well established in the literature, but the second is not. Fame appears to be important in driving citations. The remainder of Section 4, as well as Appendices 1-4, are devoted to showing that the results presented thus far are highly robust, which may not be surprising given the simplicity of our empirical design.

4.2 Combining all papers into a single sample

Throughout the manuscript we analyze papers with two and three authors separately. The reason is that the importance of author order may differ when later authors are and are not buried in the *et al* when referenced. In this section, we repeat our analysis in a more standard format with all observations combined into a single dataset and analyzed together. This also allows us to include papers with four or more authors.

In Table 4, we restrict attention to the definition of *fame* for which our results would be expected to be, and are, most pronounced. An author's fame is the count of her papers above the 95th percentile of papers published in the same year.

In column (1), we present results of a regression of a paper's citation percentile on the difference in fame between the first and later authors. For example, if a paper's authors had fame of 20, 6, and 4, in that order, then this variable would equal 20 - (6 + 4)/2 = 15. If the author order were reversed, then the variable would take a value 4 – (6 + 20)/2 = -9. As a baseline, in column (1) we do not include fixed effects. Even with no controls, the effect of fame differences and author order correlate with a paper's citations. The predictive power of this variable on its own is low – the R-squared of the regression is less than 0.001 – but the correlation is present.

In column (2) we add Journal x Year fixed effects. Both the R-squared of the regression and the association between author fame and citations increase. In column (3), we add the average fame of all of the authors. In our example with authors with fame of 20, 6, and 4, the average fame is (20 + 6 + 4)/3 = 10. The coefficient on the variable measuring the difference in fame between the first and later authors again increases. In column (4), we add a dummy variable indicating that a paper has more than two authors. A paper's number of authors has been found previously to predict its eventual citations and does so in our sample as well. Finally, in column (5), we interact this dummy variable with the difference in author fame. The coefficient on the uninteracted variable falls but the coefficient on the interaction term is considerably larger. This indicates that, while fame differences matter for two-author papers, they matter much more for papers with more authors. This is consistent with the *et al* effect and our results in Table 3.

Returning to our example of authors of varying fame, consider again three authors with 40, 20, and 10 papers. If we order authors from most cited to least, rather than the other way around, the paper's expected citation percentile would increase by nearly 15 points, similar to the expected effect using coefficient estimates in Table 3. This is a large effect, especially given that these authors would all be considered highly successful in the field. Leaving aside whether our coefficient estimates apply to the relatively small number of superstars in the sample, we can imagine instead a paper written by a rather successful scholar, with 8 home runs, and two other authors with zero. This sort of paper is common in our sample. The Fame Difference is 8 – (0 + 0)/2 = 8 if the famous author is first and 0 – (8 + 0)/2 = -4 if the famous author is second or third. The citation percentile would be nearly four points higher in the former case than in the latter. Given that all of the effect is coming from simply the author order – not the average author fame, the journal in which the paper was published, the paper's age, or its number of co-authors – we find this a large effect.

4.3 Results excluding top authors

The results discussed above suggest the concern that a few highly cited scholars may drive most of our results. Perhaps author order does matter for superstar economists, whose names are so well known that people seeing them on a page or slide may be likely to view and possibly cite the paper. Perhaps the effect is strong enough to outweigh null associations in the rest of the data. To that end, we re-analyze our sample but exclude papers written by the most famous scholars in the profession. In Table 5, we list the scholars with the most home run papers, where a home run is defined as a paper with a citation percentile above 95. Andrei Shleifer has 64 home runs, James Heckman 35, and the remainder have fewer. There is a tie for 10th with 23 home runs, so we include 14 scholars in the list.

In Table 6, we repeat the baseline analysis of Table 3 but remove all papers written by these 14 scholars. There are fewer observations, though the small magnitude of the difference indicates that the profession is much larger than these 14 people. As should be clear across all 10 regressions, the qualitative nature of the results is not changed. Author order matters, and the first author's fame is always more important than later authors' fame. The size of the effect grows as the definition of a home run is more stringent. Magnitudes of the differences are somewhat lower, though we do not present formal tests of this claim.

4.4 Results with paper fixed effects and both paper and author fame changing over time

Our baseline analysis considers citations and fame as of 2017 to all papers in our set of 48 journals. The advantage of choosing this single year is that we can use data from Web of Science, which identifies citations from all publications including those outside this set. There are two disadvantages. First, we cannot rule out the alternative explanation for our results that, for some reason, papers in which the first author is famous are simply better than those for which the second or third author is famous. Table 2 strongly suggests that this is not the case but is not dispositive. Second, many Web of Science citations appear in journals that are not widely read. Our results that fame causes citations may be more limited: perhaps fame causes citations that appear in journals with limited impact. Perhaps the citations that truly matter – those appearing in widely-read journals – reflect the true impact of the paper, not the fame of the authors.

We therefore restrict attention to citations that appear in our set of 48 journals, to papers published in that same set. The number of citations for each paper is much smaller than we observe in the Web of Science data because the set of journals in which the citations appear is much smaller, but we are able to observe the year of each citation. Furthermore, by restricting attention to only these citations, we are also restricting attention only to high-quality citations.[11]

[11] This does not imply that citations from journals outside this set are not high quality – only that citations from within this set are likely to be high quality.

We perform regressions of the form:

$$y_{its} = \alpha + \beta_1 \times Fame_{is1} + \beta_2 \times Fame_{is2} + \beta_3 \times Fame_{is3} + \gamma_i + \epsilon_{its,} \qquad (2)$$

where y_{its} is citation percentile x 100 in year $s \geq t$, for paper i, published in year t; $Fame_{isk}$ is the *fame* of the k^{th} author of paper i in year *s*; γ_i is a fixed effect for paper i and ϵ_{its} is an error.

That is to say, each observation is a paper-year. A paper published in 1998, for example, will be associated with observations in 1998, 1999, …, 2017. Each paper published before 2017 is associated with multiple observations and, for papers published before 1998, we retain only the first 20 years after publication of the paper. We include a paper fixed effect so the variation in the paper's impact is driven by changes in each author's fame over time.[12]

The interpretation of coefficients in the regression specification of Equation (2) is different from the interpretation in our baseline specification of Equation (1). Citation percentile never has a time trend, on average, but it does have a different average level across papers. The correlation of that level with the fame of each author is effectively what our work thus far has analyzed. In the specification of Equation (2), the average of level of citation percentile is removed with a paper fixed effect so if author order makes a paper more or less cited on average, *this will not be identifiable in this analysis*. Rather, we identify how *changes* in each author's fame correlate with *changes* in a paper's citation percentile over time.

To show that fame causes citations, it is not sufficient to show that the fame of a paper's authors covaries over time with the paper's citations. There are many reasons that they could covary that do not involve a causal link from fame to citations. It could happen, for example, that a particular field becomes more popular, leading to increasing fame for authors working in the area and to increasing citations to papers in the area. To show a causal effect of fame on citations, we again look to changes in the fame of first and later authors. If we find that a first author's fame correlates more over time with a paper's citations than the fame of later authors, then we have established a causal effect.

It is not obvious how to measure the fame of each author or the impact of each paper in each year of its life, so we present four analyses. A paper's impact in a given year could be measured by the citations that it receives *in that year* or by the citations that it has received cumulatively *up to that year*. Similarly, an author's

[12] Note that, because citation percentile is stationary, a paper fixed effect captures the average citation percentile over the life of a paper. It does introduce the possibility of look-ahead bias. Performing the same regressions without paper fixed effects does not materially change the qualitative results, but substantially changes the interpretations of the coefficients and the R-squareds.

fame could be measured by the citations that she receives in that year or by the citations that she has received cumulatively up to that year.

Our first specification measures a paper's impact as its citation percentile using contemporaneous citations. That is, for a paper published in 1998, we measure its impact in 2002 using its percentile ranking of citations *received in 2002* among all papers *published in 1998*. We measure each author's fame in a given year using her total citations to her other papers *in that year*, i.e., in 2002. That is, both the dependent and independent variables are contemporaneous, not cumulative. We present results of this regression in column (1) of Table 7, Panel A for two-author papers and Panel B for three-author papers. We include paper fixed effects so, whether a paper is typically 85th or 10th percentile in our sample, coefficients on each author's fame measure are not affected. Instead, variation in each author's fame drives variation in citations over time.

The advantage of using contemporaneous citations as the measure of a paper's and an author's impact in a given year is that it is "real time". As a paper ages, its citations in each year vary. Similarly, the aggregate citations that each author receives on all of her other papers in that year varies. This specification is well-designed to pick up the effect of an author quickly becoming famous on citation rates to her preexisting papers. The disadvantage is that the number of citations that a particular paper receives in a given year is often zero and variation in citation percentile is therefore noisy. The measures are therefore economically appealing but statistically unappealing.

Column (2) presents results from similar regressions in which each author's fame is measured using cumulative citations to her other papers up to the year of the observation, leaving the dependent variable as contemporaneous. Cumulative citations might be a better measure of fame, as they capture the longevity of an author's career as well as her current impact. Recognizability of a name accrues over time. Column (3) measures each paper's impact in a given year using its cumulative citations from its publication in year t to the observation year s but measures an author's fame in year s as her citations received in that year. Column (4) measures both paper impact and author fame using cumulative citations.

This last specification is most similar to our baseline analysis, as it measures both paper impact and author fame using cumulative citations. The difference is that it does so in each year of a paper's life rather than just in 2017 and considers only citations appearing in our list of 48 journals.

All 20 coefficients are positive and significantly different from zero. We do not show p-values for these tests to avoid clutter in the table, but their statistical significance is quite clear from the coefficients and t-statistics. This means that, taking each paper's average citation percentile during its life as given, papers whose authors get more famous also become more cited, relative to papers published in the same year whose authors did not get more famous. This is consistent with our hypothesis of fame causing citations. It also suggests a snowballing effect of fame: as an author gets famous, her *past papers* become more highly cited. Many of those papers retroactively become home runs that further contribute to the fame of the author. Fame builds upon itself. It is also consistent with other hypotheses, so it is not the main purpose of this table.

The purpose is to analyze the differential effect of first- and later-author fame on citations. Across all four regressions for two-author papers, presented in Table 7, Panel A, the coefficient on first-author fame is not generally larger than the coefficient on second-author fame. In fact, the coefficient on second-author fame is statistically significantly larger in column (1). There is no evidence that fame causes higher citations for first versus second authors of two-author papers in economics, and no convincing evidence of the reverse.[13]

Table 7, Panel B displays results of the same analyses for three-author papers. In each case, as in prior tables, we present results from linear restriction F-tests for the equality of coefficients on first and later authors. Across seven comparisons, the coefficient on first-author fame is significantly larger than the others. In six, equality is rejected at the 1% level and in four equality is rejected at the 0.1% level. It is fair to say that, as in our baseline analysis, the evidence that author order affects citations is clear.

Magnitudes are much more difficult to interpret in this specification. Paper fixed effects remove most of the variation due to author order. Column (1) of Table 7, Panel B, for example, tells us that, if the first author gets more famous, the effect on a paper's citations is anywhere from 177% or 75% larger than if a second or third author, respectively, experiences the same increase in fame.

5. The effect of author order on career outcomes

Our objective is to establish a causal effect of author fame on a paper's citations and the convention of alphabetical author ordering in economics and finance provides an identification strategy. The most important conclusion of the findings presented thus far is that fame matters: a paper will be more cited if the first author happens to be famous than it will be if later authors are famous, especially if the paper has at least three authors. We argue that while our method provides a strong *causal* link between fame and citations, it is almost certainly a substantial underestimate of the true effect.

That is, there are many ways that fame may cause an author to be more cited, one of which is that readers see a famous name in a literature review or on a slide at a presentation and then, in part because the name

[13] We do not have an explanation for why the coefficient on Author 2's fame is larger than the coefficient on Author 1's fame in Panel A, column (1). We present results of many tests in this paper. Sometimes noise produces unexpected results.

is familiar, read at least part of the paper and decide whether to cite it themselves. There are, of course, many other ways that fame can affect citations, most obviously that famous people are more likely to present their work at conferences and seminars and that that work is more likely to appear in prominent working paper series. Glancing at a literature review cannot plausibly be the primary way that fame affects citations.

That said, in this section we present a quantification exercise of whether the narrow effect that we identify could affect researchers' careers. We begin with a stylized model showing how to calculate the effect of fame and author order on citations. For her career success, a scholar likely wants to be first author so that her name is seen more often. This has been documented elsewhere and is not documented in this paper. Instead, we show that a scholar benefits from ordering authors of her papers from most to least famous.[14] The analysis in this section is restricted to calculating how the interaction of fame and author order affects career success and does not address any other benefits from simply being first author. That is, the career benefit for an author being listed first may outweigh a benefit from listing a famous co-author first, but we only attempt to measure the latter.

We next show descriptive statistics for how different the citations could have been for all authors in our sample as well as the subset likely to be coming up for tenure around 2017, when most of our analysis takes place. Finally, we use estimates from the literature of the impact of citations on tenure rates and salaries to provide back-of-the-envelope calculations of the possible magnitude of author ordering on tenure and pay.

5.1 A stylized model of the joint effect of fame and author order on citations

We begin with a simple model that highlights the interacting effects of author order of fame in generating citations. Suppose that a paper is written by three authors, each of whom is endowed with an inalienable type. That type has two dimensions, name and fame.

Author i has the name $n_i \in [0,1]$, which represents the percentile ranking of her name among all authors in the population. For simplicity, we assume that names are never identical, so $n_i \neq n_j$ for $i \neq j$. Author i has fame $q_i \in \mathbb{R}$, which represents her average contribution to a paper's citations, not accounting for the interacting effect of her name.

Paper j receives citations $c_j = \alpha_1 q_{1j} + \alpha_2 q_{2j} + \alpha_3 q_{3j} + \epsilon_j$, where ϵ_j is a random variable with mean 0. q_{1j} is the fame of the first author, q_{2j} is the fame of the second author, and q_{3j} is the fame of the third author. This means that expected citations are $E(c_j) = \alpha_1 q_{1j} + \alpha_2 q_{2j} + \alpha_3 q_{3j} + E(\epsilon_j)$, which is equivalent to

[14] If she happens to be the most famous author, then these effects compound and she clearly wants to be first author. If she is least famous, then there is a trade-off associated with her position among authors.

$E(c_j) = \alpha_1 q_{1j} + \alpha_2 q_{2j} + \alpha_3 q_{3j}$. Note that this model does not take a stand on why author fame relates to a paper's citations. It merely states that there is a correlation and that the correlation can depend on whether the author is listed first, second, or third.

To see how fame and author order interact, we present results of two examples. We compare expected citations for an author whose name is first in the alphabet among all authors in the profession to expected citations for an author whose name is last. We assume that an author's co-authors' fames are random i.i.d. draws from some distribution that may be author specific.

Example 1: Let author i have the name $n_i = 0$ or $n_i = 1$. If $n_i = 0$ then author i is always the first author and expected citations are:

$$E\left(c_j \middle| n_i = 0\right) = \alpha_1 q_i + (\alpha_2 + \alpha_3) E(q_{-i}).$$

If $n_i = 1$ then author i is always the last author and expected citations are:

$$E\left(c_j \middle| n_i = 1\right) = (\alpha_1 + \alpha_2) E(q_{-i}) + \alpha_3 q_i.$$

Define $\Delta c_j \equiv E\left(c_j \middle| n_i = 0\right) - E\left(c_j \middle| n_i = 1\right)$ to be the additional citations that a paper is expected to receive if author i's name is last, alphabetically, rather than first. Then,

$$\Delta c_j = (\alpha_1 - \alpha_3)\left(q_i - E(q_{-i})\right).$$

Result 1a: If $\alpha_1 = \alpha_3$, then $\Delta c_j = 0$. If either author order or author fame does not affect citations, then a paper's expected citations do not depend on author order.

Result 1b: If $\alpha_1 > \alpha_3$, then $\Delta c_j = (\alpha_1 - \alpha_3)\left(q_i - E(q_{-i})\right)$. If an author is likely to be more famous than her co-authors, then $q_i - E(q_{-i}) > 0$, in which case citations are higher when she is first author. If an author is likely to be less famous than her co-authors, then $q_i - E(q_{-i}) < 0$, in which case citations are lower when she is first author.

Result 1c: If $\alpha_1 > \alpha_3$, then $\frac{\partial \Delta c_j}{\partial q_i} = (\alpha_1 - \alpha_3) > 0$, meaning that the importance of being first rather than last in the alphabet increases linearly in the author's fame.

The preceding results allow for an author's co-authors to be random, so that q_{-i} is drawn from some non-degenerate distribution. They also allow, of course, for an author's co-authors to be known, in which case $E(q_{-i}) = q_{-i}$. In this case, the value of Δc_j does not include expectations. If the other two co-authors are labeled a and b, with $n_a < n_b$, then we have:

Result 1d: If author qualities are not random variables, then $\Delta c_j = \alpha_1(q_i - q_a) + \alpha_2(q_a - q_b) + \alpha_3(q_b - q_i)$. $\alpha_1 > \alpha_2 = \alpha_3$, then $\Delta c_j = (\alpha_1 - \alpha_3)(q_i - q_a)$. The only difference from Result 1b is that the relevant comparison author in calculating Δc_j is the co-author whose name appears earlier in the alphabet. That is because moving author i from first to last moves author a from second to first, which matters, and moves author b from third to second, which doesn't.

Example 2: We return in this example to the case where author i has name $n_i \in [0,1]$ and assume that her co-authors names are drawn from $U[0,1]$. The distribution of co-author names is without loss of generality so long as we restrict to continuous distributions over $[0,1]$.

We assume that author qualities are again drawn from some distribution that is independent of author names, so $E(q_{-i}|n_{-i}) = E(q_{-i})$ for all n_{-i}. This assumption is restrictive, but the intuition provided in this example would largely follow without it.

Expected citations depend on the likelihood that author i is first, second, or third author, her fame, and the expected qualities of the other two authors.

$$E\left(c_j \middle| n_i, q_i\right) = \iint_{n_i}^{1} \left(\alpha_1 q_i + (\alpha_2 + \alpha_3)E(q_{-i})\right) d^2 n_{-i} + \iint_{0}^{n_i} \left((\alpha_1 + \alpha_2)E(q_{-i}) + \alpha_3 q_i\right) d^2 n_{-i}$$
$$+ \int_0^{n_i} \int_{n_i}^{1} \left((\alpha_1 + \alpha_3)E(q_{-i}) + \alpha_2 q_i\right) d^2 n_{-i}.$$

The mixed partial derivative of expected citations with respect to author i's fame and name is

$$\frac{\partial^2 E(c_j)}{\partial q_i \partial n_i} = 2(\alpha_1 - \alpha_2)(n_i - 1) + 2(\alpha_3 - \alpha_2).$$

Result 2a: If $\alpha_1 = \alpha_2 = \alpha_3$, then $\frac{\partial^2 E(c_j)}{\partial q_i \partial n_i} = 0$. If either author order or author fame does not affect citations, then a paper's expected citations do not depend on author order.

Result 2b: If $\alpha_1 > \alpha_2 = \alpha_3$, then $\frac{\partial^2 E(c_j)}{\partial q_i \partial n_i} = 2(\alpha_1 - \alpha_2)(n_i - 1) < 0$. This implies that the effect of an author's fame on expected citations is decreasing as the author's last name is later in the alphabet. As in Example 1, early last names and author fame are complementary.

These results should make clear that what matters is not author order *per se*, but author order interacted with author fame: a paper should expect higher citations if its most famous author is first.

5.2 Estimating the causal impact of author ordering on citations and tenure

In this section we ask whether the combined effect of author order and fame is large enough to affect economists' careers. Einav and Yariv (2006) show that there are fewer tenured economists with late-alphabet last names at top 5 economics departments than there are untenured economists. Specifically, the realized cumulative distribution of tenured faculty at top 5 departments is first order stochastically dominated by the distribution of untenured faculty. The idea is that an early-alphabet author's last name will put both herself and her papers high on lists and therefore be visible in the profession. Assuming that this visibility is not simply a proxy for the quality of her work, this suggests that an arbitrary trait of an author – her last name – can affect her tenure at a top department, which is surprising and disturbing. Supporting this conclusion is the fact that the same is not true for psychologists, who do not use alphabetical ordering to determine the order of authors of a paper.

Our results thus far add a twist to their conclusions: having an early name is almost certainly beneficial for an author for the reasons above, but it is also beneficial *if she is the most prominent author of the paper*. The effect of having an early last name may therefore be especially large for authors at top departments. Indeed, Einav and Yariv (2006) find that the gap between the share of early-alphabet economists who are tenured and untenured disappears as the sample expands to all economists at top 35 departments. This is suggestive evidence for the interaction effect that our methodology uncovers.

We more directly estimate the degree to which author order can affect an author's aggregate career citations and present results in Tables 8, 9, and 10. Table 8 replicates our base regressions in Table 3 but replaces *citation percentile* with citations as a dependent variable. As noted in Section 3, citation percentile is an appealing choice for a left-hand side variable because citations are highly skewed and have a time trend. These facts are clearly shown in Figure 1. Citation percentile is not, however, useful for estimating the effect of author order on a scholar's overall *level* of citations.

With raw citations as the dependent variable, most of the variation resides in the small number of papers with enormous citations. Predicting the variation among this small set of papers would therefore be the objective of OLS regressions and would make the remaining observations unimportant in our estimation. To account for this skew, we winsorize citations by 1%, 2%, 3%, and 5% in the specifications of the first four columns of Table 8. We also handle the skew in citations by using $\log(1 + citations)$ as the dependent variable in the fifth column. As our preferred specification throughout the paper has been to define an author's fame as the count of her papers that are above 95th percentile among papers published in the same year, we continue to use that definition here.

As in our preceding analyses, the first author's fame matters more than later-author fame in predicting a paper's citations, regardless of how much we winsorize or whether we apply a log transformation. The differences between first- and second-author impact are highly statistically significant for two-author papers and of mixed significance for three-author papers. When we only winsorize at the 1% level, the difference is not statistically significant at conventional levels, but it becomes more significant as we truncate more outlying levels of citations. The difference between the impact of first- and third-author fame is always highly significant. The differences in magnitudes are consistently large.

As we move from 1% to 5% winsorization, the magnitudes of each coefficient shrink. This is to be expected: more and more highly cited papers have their citation levels truncated as the winsorization is increasingly strict, so the predicted levels of citations in these regressions must fall.

Now that we have estimates of how a paper's citation count depends on its authors' fame, we use these estimates to create counterfactuals: how different would we expect a paper's citations to be had the author order been different? We use coefficients from column (1) in Panel A for two-author papers and column (1) in Panel B for three-author papers. Similar results would obtain using coefficient estimates shown in other columns.

Table 9 presents an example of how we create counterfactual predictions for citations under different author orders. We return to our example paper of Kamenica, Mullinathan, and Thaler (2011) which, as of 2017, had received 14 Web of Science citations. Recall that, at that time, the fame values for Kamenica, Mullinathan, and Thaler in 2017 were 3, 11, and 23, respectively. There are five alternative author orderings that could have been chosen for this paper and we predict citations in each case.

Because this is a three-author paper, we create counterfactuals with equations like:

$$E(c_j) = \underbrace{14}_{\substack{\text{Actual} \\ \text{citations}}} + 2.932 \times \underbrace{(23 - 3)}_{\substack{\text{Actual versus} \\ \text{counterfactual} \\ \text{first author fame}}} + 2.418 \times \underbrace{(11 - 11)}_{\substack{\text{Actual versus} \\ \text{counterfactual} \\ \text{second author fame}}} + 1.935 \times \underbrace{(3 - 23)}_{\substack{\text{Actual versus} \\ \text{counterfactual} \\ \text{third author fame}}} = 33.93 \qquad (3)$$

That is, we use the actual citations and actual author order as the baseline, and then create counterfactuals using the difference in fame between the actual first author and counterfactual first author, multiplied by the coefficient on first author, etc. In the most extreme case, in which the ordering would have been Thaler, Mullinathan, and Kamenica, we predict that the paper would have received 19.93 additional Web of Science citations (as of 2017) simply from the change in author order, for a total of 33.93. All other orderings would also have produced more citations than the actual order but less than the most extreme order. This paper provides an example in which it was under-cited relative to an alternative ordering.

For each paper in our sample, we therefore have the highest and lowest expected counterfactual citations. The former always occurs when authors are ordered from most to least famous, and the latter in the reverse ordering. We then calculate the absolute value of the difference between these two numbers, which is a paper's range. In the example above, the paper would be assigned a range of 19.93. We sum all paper ranges for papers written by each author in our sample to get an author-level range: how different could an author's aggregate citations have been had all of her papers' authors been ordered from most famous to least famous, as opposed to the reverse? This author-level definition of range will hereafter be the variable to which the term *range* refers.

The first column of Table 10, Panel A, presents summary statistics for author-level range. Most scholars would not have been affected by alternate author orderings, for two reasons. First, most authors have few publications and therefore few citations. Second, most authors have not written with famous co-authors. If the author fame variables all take a value of 0, then author order does not matter. Our results matter for a scholar's career only if she is famous or if she publishes somewhat regularly with famous co-authors.

The 95th percentile author in our sample, ranked by range, would have been expected to have had 35.43 more citations in 2017 than she actually did. Is this a lot or a little? The third column of Table 10, Panel A shows summary statistics for citations in our sample: the median is 26. A 90th percentile author has 337 Web of Science citations, so a change of 35.43 simply due to author order is not small.

To better describe the size of these effects relative to people's actual citations, in the second column we divide an author's range by her actual level of citations. That is, if an author has 40 citations and would have expected 45 had the authors of all of her papers been ordered from most to least famous, and 35 had they been ordered from least to most famous, then the *percentage change in citations* (hereafter PCC) is $(45 - 35)/40 = 25\%$. We present summary statistics for this variable in the second column, dropping all authors who have never been cited. Just as in column (1), the median author is not much affected by author order because most authors have few publications, especially with famous co-authors. The top 10% of authors, however, see large percentage effects on their citations based on author order. Even if many of these authors have a low baseline of citations against which the range is compared, the effect on a scholar's career might be large. Candidates for tenure at a top 200 department with 75 citations versus 50, for example, might be viewed just as differently by their tenure committees as candidates for tenure at a top 5 department with 750 citations versus 500.

To analyze the effect on tenure decisions specifically, we perform the same analyses but restrict the sample to scholars whose first publications, solo or co-authored, were in the years 2008-2012. The idea of this restriction is that we consider only those who were likely to be considered for tenure in a year close to 2017, the year in which our Web of Science citation counts were drawn. Results are presented in Table 10, Panel B. In this sample, the median author has 20 citations and the 95th percentile author has 144. In terms of the range in citations simply due to author order, the 95th percentile author has a range of 22.15 citations, a number higher than the median level of citations. As with our full sample, the effect on a scholar's career might be large.

5.3 A back-of-the-envelope estimate of the effect of author ordering on career outcomes

In this section, we provide back-of-the-envelope estimates of the magnitude of the effect of author order on career outcomes, specifically salary and the likelihood of tenure at a scholar's first placement. To do so, we augment our analysis in the preceding section with estimates of citations on career outcomes in two other papers. We could consider other career outcomes like major awards or inductions into important societies, but these seem unlikely to be affected by citations alone. Rather, it is more likely that extra citations could be important for pay and promotion committees at schools that rely on these hard metrics in making these decisions. Many schools have explicit bonuses for publications. It would not be surprising if these or similar schools put weight on citations for promotion or pay, regardless of the cause of those citations.

We begin by considering the effect on tenure likelihoods. Sarsons *et al* (2020) use a sample of 613 scholars who go up for tenure at top-35 US economics departments and estimate the effect a variety of variables on the likelihood of tenure at first placement. One such variable is log(citations). We take the coefficient on log(citations) from Table 2, column (3) of Sarsons *et al* (2020), to be the estimated marginal effect of a 1% increase in citations on tenure likelihood. That effect is 0.057.[15]

Some authors have very little expected effect from changes in author ordering on their papers and some have large expected effects. Recall that our measure of the possible effect of ordering as a percentage change in an author's actual level of citations is called the author's PCC. Summary statistics for PCCs can be found in Table 10, Panel B, column (2) of this paper. To estimate the maximum possible effect of alternative author orders on a scholar's likelihood of tenure, we multiply 0.057 by the author's PCC. The median author's PCC is 0 so the effect of optimal ordering on her tenure likelihood is $0.057 \times 0\% = 0\%$, meaning that author order is completely irrelevant for the median author's citations. The 95th percentile of PCC is 63.24 so the effect of optimal ordering on her tenure likelihood is $0.057 \times 63.24\% = 3.6\%$.

[15] We focus on column (3) because it uses the full sample of economists who went up for tenure as well as fixed effects for tenure institution, tenure year, and field. Sarsons *et al* (2020) use Google Scholar as their source of citations but the estimate on percentage changes in the number of citations should extend to Web of Science as well.

These numbers are consistent with the idea that author order and the fame effect are jointly irrelevant for the typical author but could be quite important for certain authors. To take a concrete example, a 95th percentile author with 80 citations at the time she comes up for tenure would have an expected citation range of $80 \times 63.24\% = 50.59$. She might have had, for example, 110 citations had her author orders been optimal or 59 or 60 had her author orders been as bad as possible. This is a fairly large range, which may not be inconsistent with a gap in the likelihood of tenure from the worst case to the best of 3.6%. This change in the likelihood of tenure from what seems so minor and arbitrary is almost implausibly large, but we emphasize that this is the difference stemming from the absolute best author order to the absolute worst, *on all papers, for an author whose citations are highly responsive to this effect*. This will only occur in the cases of authors who are either very famous or not at all famous and have either very early or very late names in the alphabet. For most authors who are either very famous or not at all famous, the effect would typically be about half of this size. Our example author with 80 actual citations would have benefited by 30 citations in the best-case counterfactual, which would increase her likelihood of tenure by $0.057 \times \frac{30}{80} = 2.1\%$. She could have been worse off by $0.057 \times \frac{20.59}{80} = 1.5\%$. These numbers are still large, but somewhat more palatable.

We also consider the potential effect of author order on salaries of full professors. Hamermesh and Pfann (2012) study a sample of 564 full professors at the 88 US institutions ranked top 200 worldwide for whom salary data are available. They regress Log(salary) on Total Citations/100 and several other variables. We use column (1) in Table 6 of Hamermesh and Pfann (2012) as our preferred regression of the impact of citations on Log(salary), and in that regression the coefficient on Total Citations/100 is 0.0208. We use the range of citations reported in Table 10, Panel B, column (1) of this paper as our preferred estimates of the potential difference in citations based on fame and author order and use the median and 95th percentile values to estimate the expected effect on salary for these authors. The median range is 0, consistent with the median percentile range discussed above. The 95th percentile range is 22.15. The expected change in log(salary) based only on the author order is therefore $(0 \times 0.000208) = 0$ for the median author and $(22.15 \times 0.000208) = 0.0046$ for the 95th percentile author, which implies a 0.46% increase in pay.

An important caveat to the preceding back-of-the-envelope analysis is that tenure committees may weigh citations to papers written with famous co-authors less than citations to papers written without famous co-authors. The average effects of citations on tenure and pay may be averages of larger effects when papers have no famous authors and smaller effects when they have at least one. The fact that fame causes citations over and above the quality of a paper gives committees good reason to do this weighting, so we would not be surprised if the practice were common.

Summarizing the results in this section, most authors are not much affected by the fact that fame matters. Most authors are not famous, and they do not co-author with famous people. As shown in the existing literature, it pays to have an early last name so that one's name is seen more often, appears earlier in lists, etc., but this effect is separate from what we document. What we show is that, conditional on having a famous author on a paper, putting that author first can have a first-order effect on a scholar's citations, even as early as the time she is considered for tenure. For a small subset of authors, this may have a meaningful effect on the likelihood of tenure. It may also influence pay. We caveat these results with the fact that estimates in our paper, Sarsons *et al* (2020), and Hamermesh and Pfann (2012) are not precise – we use point estimates to generate these estimates, each paper uses only a selected sample of scholars in its analysis, and the samples in the three papers only partly overlap. These estimates should be taken as back-of-the-envelope, not gospel.

5.4 The choice of author ordering

The results throughout the paper show that a paper is cited more if its most famous author is cited first. Because author order is alphabetical and therefore quasi-random, this is clean evidence that fame is causally affecting citations. The overall effect of fame on citations is likely to be much larger than the effect acting only through the interaction of fame and author order. That said, in Sections 5.2 and 5.3, we showed that the effect on an author's likelihood of tenure can be large, suggesting that authors might want to choose alternative author orders deliberately to maximize expected citations.

Consider the decision of a three-author team sending a final version of a paper to a journal – what order should they list themselves in? To our knowledge, all journals allow the authors to choose an ordering themselves. Alphabetical ordering is conventional but not mandatory, and it is not hard to find a paper in any of the 48 journals in our list that bucked the convention. It is tempting to conclude that, to maximize the paper's citations, the authors should be listed from most famous to least famous.

We do not believe that this conclusion is supported by our results. Non-alphabetical ordering, because it is unusual, may be seen as a signal by the reading public. It is a choice and choices are often viewed as conveying information. In fact, the full citation of Sarsons *et al* (2020) is Sarsons, Gërxhani, Reuben, and Schram (2020), which is not alphabetical. The history of this paper, discussed in its acknowledgements, is reflected in the order of its authors' names. The analysis in Sections 5.2 and 5.3 asks the question "what if the authors on this paper were ordered differently, by some process unrelated to the content of the paper?" The process of Ray and Robson (2018) is an example of how this could be done. We do not estimate effects from a chosen order. For example, in lab sciences, the first (and often last) author of a paper has special significance, relative to other locations in the list of authors. A famous first author may well indicate important information about the quality of the paper.

The choice of author order could be removed by journals who change the default from alphabetical ordering to fame ordering. This would maximize citations to the journal. So long as the authors have no control, or at least so long as the default is heeded most of the time, this strategy could be effective. It would also be fraught as there are several measures of fame and author fame changes over time. It is especially fraught because there is a well-known advantage to being first author, regardless of fame. A less famous person being first author on a paper might not maximize citations to that paper, but it would increase citations to her other work. It seems patently unfair to reward authors who are already famous with the additional benefit of persistent first authorship.

Individuals themselves could attempt to increase citations by strategically choosing co-authors. Famous authors should prefer co-authors with later names in the alphabet and less famous authors should prefer famous authors with names earlier in the alphabet. While this two-dimensional assortative matching may be theoretically possible, it seems like an implausible description of how scholars collaborate. The effect on citations of more complementary skills is likely much larger than the effect of better author ordering.

6. Conclusion

A paper in finance, accounting, and economics, fields in which author order is typically alphabetical, is cited more if its most famous author appears first. Given that people are more attentive to the first item in a list, and that author alphabetization is unrelated to quality, we therefore provide evidence that fame causes citations.

Because we find large effects on a paper's citations simply by changing the ordering of authors within a paper, the effect in the ideal experiment, in which known authors are replaced with unknown authors, would likely be much larger. In short, our estimates probably underestimate the effect of fame on citations substantially.

Perhaps fame causes citations because people tend to cite a paper when they recognize the name associated with it. If so, this does not imply that citers are making mistakes: familiar names probably write more interesting and better-executed papers. Given limited attention, it is individually rational to read, and therefore cite, papers written by more familiar names.

While it may be rational for an individual not to read a manuscript written by unfamiliar names, this behavior likely results in high-quality manuscripts failing to receive the recognition that they deserve. This cautions against using citations in promotion and tenure decisions and instead reading the papers themselves.

Early fame is likely to have effects on the careers of newly minted faculty. Citations directly affect tenure, promotion, and hiring decisions. A few highly public early years in one's career, perhaps via a large interview set on the job market, membership in the NBER, or early success in conference submissions, may make or break that career. These effects are first-order for the individual and may have first-order effects on the composition of the academy: pregnancy and child rearing, for example, are more limiting for women's than men's early career networking. If this substantially affects women's citations and citations are taken as an objective measure of impact by tenure committees, then the profession will disproportionately tenure men.

Our analysis was limited to scholars publishing in economics, finance, and accounting journals, but there is no reason to believe that the causal impact of fame on citations is limited to these fields. They merely provide a laboratory in which we can make causal claims. The policy analysis in the preceding paragraphs should therefore not be limited to departments in these fields.

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Figure 1: Raw Citations at various citations percentiles by year of publication

This figure plots the level of citations to papers at various percentiles. The data include all journals in our sample, and all papers published in these journals on and after the year since 1974.

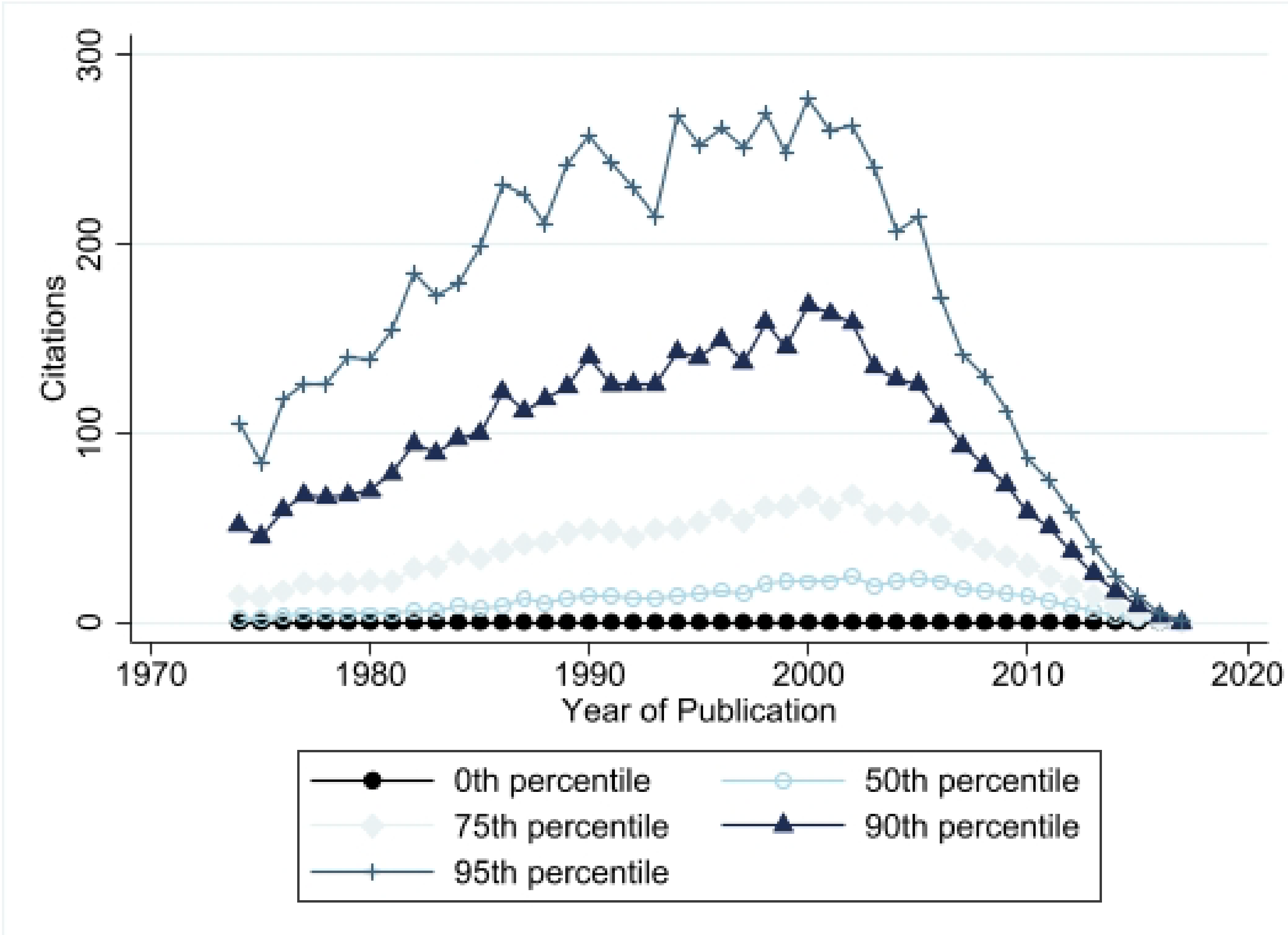

Table 1: List of journals

This table reports all included journals, and the first year in which the journal appears in our dataset. Our dataset begins in the year 1974.

Journal Name		Journal Name	
ACCOUNTING REVIEW	1974	JOURNAL OF FINANCIAL ECONOMETRICS	2007
AMERICAN ECONOMIC JOURNAL	2009	JOURNAL OF FINANCIAL ECONOMICS	1976
AMERICAN ECONOMIC REVIEW	1974	JOURNAL OF FINANCIAL INTERMEDIATION	1995
ECONOMETRICA	1974	JOURNAL OF FINANCIAL MARKETS	2002
ECONOMIC JOURNAL	1974	JOURNAL OF FINANCIAL RESEARCH	1984
ECONOMIC THEORY	1995	JOURNAL OF HUMAN RESOURCES	1974
FINANCIAL ANALYSTS JOURNAL	2001	JOURNAL OF INDUSTRIAL ECONOMICS	1974
FINANCIAL MANAGEMENT	1974	JOURNAL OF INTERNATIONAL ECONOMICS	1974
GAMES AND ECONOMIC BEHAVIOR	1991	JOURNAL OF LABOR ECONOMICS	1983
INTERNATIONAL ECONOMIC REVIEW	1977	JOURNAL OF LAW & ECONOMICS	1974
JOURNAL OF ACCOUNTING & ECONOMICS	1982	JOURNAL OF MONETARY ECONOMICS	1976
JOURNAL OF ACCOUNTING RESEARCH	1974	JOURNAL OF MONEY CREDIT AND BANKING	1976
JOURNAL OF APPLIED ECONOMETRICS	1987	JOURNAL OF POLITICAL ECONOMY	1974
JOURNAL OF APPLIED ECONOMICS	2005	JOURNAL OF PUBLIC ECONOMICS	1974
JOURNAL OF BANKING & FINANCE	1980	MANAGEMENT SCIENCE	1974
JOURNAL OF BUSINESS	1974	MATHEMATICAL FINANCE	1997
JOURNAL OF BUSINESS & ECONOMIC STATISTICS	1985	QUARTERLY JOURNAL OF ECONOMICS	1974
JOURNAL OF CORPORATE FINANCE	2001	RAND JOURNAL OF ECONOMICS	1984
JOURNAL OF ECONOMETRICS	1980	REVIEW OF ECONOMIC DYNAMICS	2001
JOURNAL OF ECONOMIC GROWTH	1999	REVIEW OF ECONOMIC STUDIES	1974
JOURNAL OF ECONOMIC LITERATURE	1974	REVIEW OF ECONOMICS AND STATISTICS	1974
JOURNAL OF ECONOMIC PERSPECTIVES	1988	REVIEW OF FINANCE	2008
JOURNAL OF ECONOMIC THEORY	1974	REVIEW OF FINANCIAL STUDIES	1988
JOURNAL OF FINANCE	1974		
JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS	1974		

Table 2: Summary statistics

This table reports the summary statistics for each variable used in the regression specifications. For two-author papers, we report summary statistics for a count of the number of papers excluding the current paper which are above the 0th (50th, 75th, 90th, 95th) percentile by the first author (Author 1), and the second author (Author 2). We report the same statistics for three-author papers in our sample.

		Two-Author Papers		Three-Author Papers		
		Author 1	Author 2	Author 1	Author 2	Author 3
		N = 39,046		N=16,920		
Papers above 0th Percentile	Mean	15.08	15.26	13.48	13.15	13.00
	Median	9.00	9.00	8.00	7.00	7.00
	Std Dev	17.43	18.64	16.38	16.59	16.78
	Min	0	0	0	0	0
	Max	128	128	128	128	128
Papers above 50th Percentile	Mean	9.58	9.64	8.67	8.33	8.28
	Median	5.00	5.00	4.00	4.00	4.00
	Std Dev	13.00	13.71	12.14	12.06	12.28
	Min	0	0	0	0	0
	Max	117	117	104	117	117
Papers above 75th Percentile	Mean	5.65	5.57	5.17	4.86	4.81
	Median	2.00	2.00	2.00	2.00	2.00
	Std Dev	9.29	9.49	8.65	8.53	8.64
	Min	0	0	0	0	0
	Max	101	101	77	101	101
Papers above 90th Percentile	Mean	2.63	2.57	2.39	2.28	2.30
	Median	1.00	0.00	0.00	0.00	0.00
	Std Dev	5.60	5.65	5.02	5.45	5.52
	Min	0	0	0	0	0
	Max	83	83	52	83	83
Papers above 95th Percentile	Mean	1.43	1.39	1.29	1.24	1.26
	Median	0.00	0.00	0.00	0.00	0.00
	Std Dev	3.69	3.69	3.22	3.75	3.75
	Min	0	0	0	0	0
	Max	64	64	35	64	64

Table 3: Author fame and paper citations – Baseline

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. In Panel A, we include two-author papers and in Panel B, three-author papers. In each column, fame is defined as the number of papers with citations weakly above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50 ,75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citation percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	17.083	28.410	42.047	65.548	90.966
	(0.737)	(0.988)	(1.428)	(2.629)	(4.326)
Author 2: Fame	12.861	22.328	34.878	54.595	75.092
	(0.663)	(0.906)	(1.363)	(2.442)	(3.837)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.000***	0.000***	0.001***	0.006***	0.012**
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39,046	39,046	39,046	39,046	39,046
R-squared	0.268	0.282	0.288	0.284	0.278

Panel B: Three-author papers

Dependent Variable: Citation percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	13.315	23.085	35.673	61.682	95.164
	(1.222)	(1.652)	(2.338)	(4.058)	(6.510)
Author 2: Fame	8.796	17.520	29.433	42.377	56.202
	(1.229)	(1.628)	(2.309)	(3.821)	(5.797)
Author 3: Fame	6.915	14.070	23.066	33.920	41.393
	(1.161)	(1.564)	(2.226)	(3.461)	(4.975)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.012**	0.022**	0.073*	0.001***	0.000***
Author 1 and Author 3	0.000***	0.000***	0.000***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,920	16,920	16,920	16,920	16,920
R-squared	0.291	0.302	0.311	0.309	0.306

Table 4: Author fame and paper citations – combined regressions

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. We define a home run as a paper with a citation percentile weakly above 95 and define the fame of an author to be her number of home runs not including the paper in question. *Fame Difference* is the difference in fame between the first author and the later authors, *Fame Average* is the average fame value of the paper's authors, and *More than 2 Authors* is an indicator variable that takes a value of 1 if the paper has more than 2 authors and zero otherwise. All specifications include Journal x Year fixed effects. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

Dependent Variable: Citation percentile	(1)	(2)	(3)	(4)	(5)
Fame Difference	6.727**	9.024***	14.876***	14.936***	8.204**
	(2.931)	(2.445)	(2.666)	(2.649)	(3.214)
Fame Average			171.853***	171.835***	173.226***
			(4.401)	(4.372)	(4.322)
More than 2 Authors				337.540***	336.770***
				(20.803)	(20.798)
Fame Difference x More than 2 Authors					24.342***
					(5.464)
Journal x Year FE	No	Yes	Yes	Yes	Yes
Observations	59,218	59,218	59,218	59,218	59,218
R-squared	0.000	0.230	0.260	0.264	0.264

Table 5: Most famous authors

This table reports the names of top authors in our sample ranked by total home runs, defined as papers with citation percentile weakly above 95. We report the number of papers by the author weakly above the Xth percentile where X is equal to 0, 50 ,75, 90, and 95 in columns (1), (2), (3), (4) and (5) respectively.

Author	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
SHLEIFER, A	128	117	101	83	64
HECKMAN, J	129	104	77	52	35
FAMA, EF	83	75	64	49	33
STULZ, R	99	84	67	46	32
TIROLE, J	116	100	75	53	29
ACEMOGLU, D	111	97	73	41	27
STIGLITZ, J	129	107	78	36	27
CAMPBELL, JY	71	56	51	35	26
FRENCH, KR	48	44	39	32	24
BARRO, R	74	64	55	37	23
ENGLE, R	77	64	49	31	23
STEIN, JC	62	58	45	35	23
THALER, R	70	59	48	35	23
VISHNY, RW	34	31	30	24	23

Table 6: Author fame and paper citations – dropping most famous authors

The dependent variable in all specifications is Citation percentile, the citation percentile of the paper multiplied by 100. In Panel A, we include two-author papers and in Panel B, three-author papers. In each column, fame is defined as the number of papers with citations weakly above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50 ,75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. We exclude papers by top authors, listed in Table 5. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citation percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	16.930	30.697	49.307	87.960	134.789
	(0.814)	(1.132)	(1.668)	(3.020)	(4.878)
Author 2: Fame	12.788	25.268	44.297	80.966	115.950
	(0.758)	(1.093)	(1.703)	(3.196)	(5.070)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.000***	0.001***	0.056*	0.152	0.016**
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	38,529	38,529	38,529	38,529	38,529
R-squared	0.261	0.276	0.286	0.286	0.280

Panel B: Three-author papers

Dependent Variable: Citation percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	13.967	26.000	41.825	73.842	118.177
	(1.362)	(1.888)	(2.706)	(4.826)	(8.082)
Author 2: Fame	7.610	17.519	33.798	60.987	94.198
	(1.370)	(1.956)	(2.952)	(5.371)	(8.703)
Author 3: Fame	5.909	14.649	28.418	50.462	68.571
	(1.329)	(1.947)	(3.039)	(5.486)	(8.645)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.002***	0.003***	0.062*	0.099*	0.064*
Author 1 and Author 3	0.000***	0.000***	0.002***	0.003***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,676	16,676	16,676	16,676	16,676
R-squared	0.285	0.297	0.307	0.308	0.306

Table 7: Author fame and paper citations over time

The dependent variable is Citation percentile, the citation percentile of the paper multiplied by 100. In Panel A, we include two-author papers and in Panel B three-author papers. We define the fame of an author to be the count of citations received by all of her papers not including the paper in question. In each column, for the dependent and independent variables, we use either the count of the number of citations received by each paper in the current year or the running total of the number of citations received by the paper up to and including the current year. Standard errors, clustered at the paper level, are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citation percentile	(1)	(2)	(3)	(4)
Author 1: Fame	4.923	0.196	5.816	0.786
	(0.442)	(0.036)	(0.429)	(0.052)
Author 2: Fame	6.807	0.225	6.300	0.785
	(0.379)	(0.036)	(0.371)	(0.044)
p-value for test of difference in coefficients of				
Author 1 and Author 2	0.003***	0.627	0.436	0.990
Paper FE	Yes	Yes	Yes	Yes
Dependent variable cumulative	No	No	Yes	Yes
Independent variable cumulative	No	Yes	No	Yes
Observations	564,859	564,859	564,859	564,859
R-squared	0.476	0.474	0.831	0.832

Panel B: Three-author papers

Dependent Variable: Citation percentile	(1)	(2)	(3)	(4)
Author 1: Fame	8.781	0.274	7.704	1.023
	(0.703)	(0.072)	(0.608)	(0.081)
Author 2: Fame	3.381	0.109	3.314	0.370
	(0.636)	(0.051)	(0.536)	(0.073)
Author 3: Fame	5.489	0.297	4.852	0.585
	(0.581)	(0.063)	(0.540)	(0.077)
p-value for test of difference in coefficients of				
Author 1 and Author 2	0.000***	0.094*	0.000***	0.000***
Author 1 and Author 3	0.001***	0.822	0.001***	0.000***
Paper FE	Yes	Yes	Yes	Yes
Dependent variable cumulative	No	No	Yes	Yes
Independent variable cumulative	No	Yes	No	Yes
Observations	192,719	192,719	192,719	192,719
R-squared	0.498	0.496	0.826	0.827

Table 8: Author fame and raw paper citations

The dependent variable in columns (1), (2), (3), and (4) is citations winzorized at y% and (100-y)% where y is 1, 2, 3, and 5 respectively. The dependent variable in column (5) is the natural logarithm (1+ citations) multiplied by 100. We define a home run as a paper with a citation percentile weakly above 95 and define the fame of an author to be her number of home runs not including the paper in question. In Panel A, we include two-author papers and in Panel B, three-author papers. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

	Citations winsorized at y% and (100-y)%				Log(1 + Citations)
y =	1%	2%	3%	5%	
Author 1: Fame	4.017	3.171	2.667	2.027	5.605
	(0.200)	(0.151)	(0.125)	(0.093)	(0.256)
Author 2: Fame	3.010	2.465	2.098	1.586	4.528
	(0.189)	(0.144)	(0.119)	(0.087)	(0.233)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.001***	0.002***	0.003***	0.002***	0.001***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39,046	39,046	39,046	39,046	39,046
R-squared	0.310	0.336	0.352	0.365	0.455

Panel B: Three-author papers

	Citations winsorized at y% and (100-y)%				Log(1 + Citations)
y =	1%	2%	3%	5%	
Author 1: Fame	2.932	2.401	2.082	1.665	4.922
	(0.256)	(0.194)	(0.162)	(0.124)	(0.329)
Author 2: Fame	2.418	1.891	1.572	1.141	3.175
	(0.268)	(0.191)	(0.154)	(0.110)	(0.310)
Author 3: Fame	1.935	1.521	1.248	0.937	2.378
	(0.259)	(0.186)	(0.145)	(0.104)	(0.263)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.195	0.079*	0.032**	0.003***	0.001***
Author 1 and Author 3	0.010***	0.002***	0.000***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,920	16,920	16,920	16,920	16,920
R-squared	0.414	0.435	0.448	0.465	0.596

Table 9: Counterfactual citations – An example

This table provides an illustrative example of actual and counterfactual citations. We consider one paper in our sample, Kamenica, Mullainathan, and Thaler (2011), entitled "Helping consumers know themselves," published in the *American Economic Review*. In columns (1) to (3), we note the potential ordering of authors. For each row corresponding to a given choice of author order, we calculate the predicted citations using the specification in the first column of Table 8 (1% winsorization), reporting the prediction in column (4). The first row shows the actual author ordering and column (4) shows the actual citations. In column (5), we report the difference between the predicted citations in column (4) and the actual citations, as shown in the first row of column (4).

Choice of author order	Author 1	Author 2	Author 3	Actual or predicted citations	Predicted minus actual citations
	(1)	(2)	(3)	(4)	(5)
Actual	Kamenica, E	Mullainathan, S	Thaler, R	14	0
Counterfactual 1	Kamenica, E	Thaler, R	Mullainathan, S	19.80	5.80
Counterfactual 2	Mullainathan, S	Kamenica, E	Thaler, R	18.11	4.11
Counterfactual 3	Mullainathan, S	Thaler, R	Kamenica, E	27.77	13.77
Counterfactual 4	Thaler, R	Kamenica, E	Mullainathan, S	30.07	16.07
Counterfactual 5	Thaler, R	Mullainathan, S	Kamenica, E	33.93	19.93

Table 10: Summary statistics for counterfactual citations at the author level

The table presents statistics for the sum of counterfactual citations for each author. For each paper, we use estimates from equation (3) to find the level of counterfactual citations with different author ordering. The range for the counterfactual citations for a paper is defined as its maximum minus the minimum counterfactual citations. The range for an author is the sum of her paper's ranges. These statistics concern author-level data. Column (1) provides statistics for the range of counterfactual citations; column (2) for the range of counterfactual citations divided by the total number of citations received by the author; column (3) provides statistics for authors' total number of citations. In Panel A, we include all authors, Panel B includes papers by authors who had their first paper published within the period 2008 to 2012.

	Range of citations	Percentage change in citations	Total number of citations
Panel A: All papers	(1)	(2)	(3)
Mean	9.26	15.43	167.19
p95	35.43	53.55	686.00
p90	17.06	24.91	337.00
p75	4.03	6.68	103.00
p50	0.00	0.23	26.00
p25	0.00	0.00	6.00
p10	0.00	0.00	1.00
p5	0.00	0.00	0.00
Panel B: All papers by authors who had their first paper within 2008 to 2012			
	(1)	(2)	(3)
Mean	4.50	14.78	40.53
p95	22.15	63.24	144.00
p90	12.05	33.55	95.00
p75	3.99	11.83	47.00
p50	0.00	0.00	20.00
p25	0.00	0.00	9.00
p10	0.00	0.00	3.00
p5	0.00	0.00	2.00

Appendix

In this appendix, we consider some additional specifications and robustness analyses. The broad implications of the paper are not affected by any of the results presented in this appendix. As in the body of the manuscript, there is sometimes stronger or weaker statistical significance for a given test, though it is usually strong. Some analyses substantially limit the number of observations and lack statistical power. Others buttress arguments made in the body of the paper but were considered too peripheral to demand space in the main document.

Appendix 1: Four-author papers

In this appendix, we repeat our baseline analysis for four-author papers. In most of our analyses, we consider only two- and three-author papers because papers with more than three authors are too rare to offer sufficiently powerful tests. In Table 4 we combine all papers with at least two authors, but we prefer using the same style of analysis throughout the paper, so we typically split two- and three-author papers into separate groups. In this appendix we repeat the analysis of Table 3 but for four-author papers. Results of our standard regressions are displayed in Table A1.

The number of observations falls to 3,252, significantly limiting the power of our F-tests. In the analyses in the body of the manuscript, the coefficient on first-author fame is typically higher than the coefficient on later-author fame, and all coefficients grow larger as fame is defined more strictly. These facts are mostly present for four-author papers as well. The only difference is that the coefficient on third-author fame is sometimes higher than the coefficient on first-author fame. In our preferred definition of fame, which is the count of an author's 95^{th} percentile papers, the coefficient on first-author fame is much larger than the coefficients on second- and fourth-author fame, somewhat larger than the coefficient on third author fame, and statistically significantly larger than fourth author fame.

There are not enough observations to make the case that fame causes citations using only four-author papers. There is not much power, given the small number of four-author papers, but the evidence is suggestive.

Appendix 2: Alternatives to citation percentile as a measure of a paper's impact

It is not obvious how best to measure the success of a paper. If we use citations, which we do in this paper (though we argue that our results should cause us to treat them skeptically), we must understand three important facts. First, time matters: as a paper ages, it accumulates citations. This means that older papers will tend to have higher citations. A claim that paper A is more impactful than paper B because it has more citations is unsatisfying if paper A was written in 1998 and paper B in 2015. Second, citations are skewed. Some papers receive thousands of citations and many or most papers receive zero, at least in Web of Science. Third, citations depend on possibly irrelevant factors. The number of authors on a paper, for example, correlates highly with citations, no matter the controls that are included.

In our analyses, for the most part, we use citation percentile. We rank all papers published within a given year by citations as of 2017 (or, in Section 4, as of the year of the observation in the panel). This accounts for the tendency of citations to accumulate over time. 5% of papers published in 2015 are considered top 5%, just as 5% of papers published in 1995 are considered top 5%. This also accounts for skew, as percentiles are forced to be uniformly distributed over the interval [0,1].

We could have used a different approach. In this appendix, we present results with some alternatives.

2.1: Measuring a paper's success using citations per year since publication

Table A2 presents results of analyses in which papers are ranked by citations per year since publication. That is, a paper published in 2015 with 12 citations would have, in 2017, 12/2=6 citations per year. A paper published in 1995 with 110 citations would have, in 2017, 110/22=5 citations per year. All papers are then ranked by citations per year and assigned percentiles within our sample.

In Panels A and B we repeat our analysis of Table 3 but using this measure of impact. We do not include Journal x Year fixed effects. Results are similar to those of the base specification, with the coefficients on first-author fame always larger than coefficients on second- and third-author fame, and coefficients increasing as fame is defined more strictly. As happens in some analyses in the paper, there is not always statistical significance at conventional levels when we perform F-tests for the differences in coefficients. Of the 15 F-tests we perform, one is not significant at the 10% level and another is not significant at the 5% level.

Our hypothesis throughout the paper is that results ought to be stronger for three or more author papers because later authors are often replaced with *et al* when papers are referenced. That is the case here.

Panels C and D include Journal x Year fixed effects. Results are similar to those in Panels A and B and those in the rest of the paper. The coefficient on first-author fame is always largest and all coefficients are growing as fame is defined more strictly. Of 15 F-tests for differences of coefficients, one is not significant at the 10% level and three are not significant at the 5% level. The remaining 11 are significant at the 5% level.

2.2: Restricting the sample to papers that have had time to age

An alternative solution to the problem of citations increasing as a paper matures is to simply restrict the sample to older papers. In Table A3, we define an author's fame by her number of top 5% publications as measured by citation percentile. In Columns (1), (2), (3), (4), and (5), we drop all papers published after 2011, 2010, 2009, 2008, and 2007, respectively. All of our standard results continue to hold. Statistical significance is weaker for two-author papers, though all F-tests reject that the coefficients on first and later authors are the same at the 10% level, and usually at the 1% level.

2.3: Using citation percentile within a journal-year rather than within a year

Our final alternative to measure a paper's impact is to calculate its citation percentile within a journal-year, rather than within a year. The idea here is that the journal itself can drive citations over and above the quality of the paper. Our base specification of citation percentile allows for many top 5% publications in, for example, *American Economic Review* while there are fewer in *International Economic Review*. To address this concern, we calculate a paper's citation percentile among all papers published in the same journal-year, rather than only in the same year. Results are presented in Table A4.

As with other analyses, the results are similar to our baseline results. The coefficient on first author fame is always larger than other coefficients and all coefficients increase as fame is defined more strictly. In this analysis, most F-tests reject coefficient equality at the 1% level, with two rejecting equality at the 5% level and one at the 10% level.

Appendix 3: Regressions using controls

Throughout the manuscript we have performed regressions with no controls beyond Journal x Year fixed effects. In Table A5, we repeat our baseline analyses but add (i) a dummy variable indicating whether an article was a lead article, (ii) the number of years since an article's publication, (iii) the journal's impact factor, measured by SCIMAGO in 2015, and (iv) the average age of all authors, measured relative to their first publications. Because two of these controls would be subsumed by Journal x Year fixed effects, we drop these fixed effects.

A paper's citation percentile is higher if it is a lead article, is published in a higher impact journal, has been longer in print, and has younger authors, all conditional on the fame of the paper's authors. The first two are not surprising but the last two are unexpected. Given that we measure a publication's impact using citation percentile, which does not have a time trend, it is not obvious that older articles should be more impactful. Almost certainly the issue is multi-collinearity between article age and author age – article age increases by 1 and author age decreases by 1 for each year that a paper was published prior to 2017.

Accurately measuring the coefficients on these controls is not the point of this exercise. Instead, we want to be sure that adding them does not materially change the relationship between first- and later-author fame. As shown in Table A5, after these controls are included, it continues to be the case that the first author's fame matters more than second- or third- author fame and that author fame matters more when we define fame more strictly. In Table A6, we repeat this analysis except that we add Journal x Year fixed effects and drop the subsumed controls. Results continue to hold.

In Table A7 we account for journal impact in a different way than in Table A5. Rather than adding impact factor as a control, we separate our 48 journals into above- and below-median groups, as measured by impact factor. It is not obvious which impact factor best measures journal quality so we use three. In columns (1) and (2), we split journals by their SCIMAGO impact factors, as calculated in 2015. In columns (3) and (4), we split based on SCIMAGO impact factors, as calculated in 2019. In columns (5) and (6), we split based on RePEc impact factors in 2022. In each case, the earlier column includes only articles published in above-median journals and the latter column includes only articles published in below-median journals. For example, the sample for column (1) includes only articles published in the 24 journals ranked above-median by SCIMAGO in 2015.

Regardless of the measure of impact, it is clear that the first author's fame matters more than later-author fame. The difference is only statistically significant in half of the analyses when there are two authors, but it is highly significant in all but one case when there are three authors. As in other analyses presented in these appendices, the main results or out paper continue to hold.

It is interesting to note that author fame matters more when a paper is published in a less prestigious journal, as measured by impact factor. In all comparisons, coefficients on author fame are larger, often much larger, for below-median journals than above-median journals. People are more likely to cite work by famous authors regardless of the journal, but the correlation is much larger for papers published in less prestigious journals. A paper published in International Economic Review is typically cited less than those published in American Economic Review, but the gap is smaller when the paper has Andrei Shleifer as an author. The causal impact of fame on citations depending on journal impact factor is not well identified in these regressions because we cannot rule out that the difference in underlying article quality when written by more and less famous people differs by journal prestige. The results are merely intriguing.

Appendix 4: Using actual author order rather than forcing alphabetical ordering

Most papers in our sample feature alphabetically ordered authors, but not all. Given the power of the alphabetical ordering convention, papers that appear with authors in another order might systematically differ from those with alphabetically ordered authors. When authors choose the ordering of their names, that ordering may convey meaning that correlates with a paper's quality and this would invalidate our identifying assumption. [See Section 5.4] The alphabetical ordering convention is why we can write this paper about economics and finance and not, for example, psychology or biology, fields in which a paper with a famous first author is fundamentally different from one with a famous second author.

In our sample, when a paper's authors appear non-alphabetically in print, we change the order to be alphabetical. Using actual author order rather than forcing alphabetization could improve the fit of our model because it would accurately account for which author is more famous, but it would call into question our causal interpretation of the results. That said, in Table A8 we re-do the analysis of Table 3 but use actual author order.

Results are similar: the first author's fame matters more for a paper's citations than later-author fame and fame correlates with citations more strongly when it is defined more strictly. R-squareds do not change from each regression in Table 3 to its corresponding regression in Table A8.

Appendix 5: Additional citations for a non-famous author with a famous last name

Our running hypothesis is that people choose what papers to cite in part based on the fame of the authors. One mechanism by which this might occur is that an author is at a talk or reading a literature review and sees a reference to a paper that may be relevant for her own work. If she notices a well-known name, then she is more likely to seek out the paper and read it. If it is relevant for her work, then she will cite it. This mechanism would imply that having a famous last name would generate citations regardless of whether the owner of that name is herself famous. Either way, the name causes readers to investigate the paper further. That is, Adrian Shleifer could be overly cited simply for having the last name Shleifer.

To investigate this possibility, we define a *superstar* author as one who is in the 95th percentile of all authors when measured by the number of top 5% publications. That is, we define an author's fame as her number of top 5% publications, which is our preferred definition throughout the paper, and define a superstar to be an author in the top 5% of fame. Our question is what happens when an author shares a last name with a superstar.

In Table A9, we make two changes to our baseline specifications in Table 3. First, we include as right-hand-side variables dummy variables taking a value of 1 if the author shares a last name with a superstar and a value of 0 otherwise. Second, we drop all superstars from the sample, so we are only considering authors who are not superstars.

Whether a paper has two or three authors, the fame of the first author still correlates more highly with a paper's citation percentile than the fame of later authors, though the difference is much smaller and not generally statistically significant at conventional levels. This is to be expected: most of our result lies within the set of papers for which at least one author is famous enough that her name is immediately recognizable to an academic reader. These are primarily superstars, and they are excluded from this analysis.

The purpose of Table A9 is to determine whether sharing a last name with a superstar causes a scholar to be cited. For two-author papers, either author sharing the last name of a superstar is associated with lower, not higher, citations. None of these eight coefficients is statistically different from zero at conventional levels. The coefficient for author 1 sharing a famous last name is also never statistically different from the coefficient for author 2 sharing a famous last name. For three-author papers, coefficients are positive if the first author has a famous last name and negative if the second or third author has a famous last name. Of the 15 coefficients, one is statistically different from zero at the 5% level.

The frequency of sharing a famous last name is low so these are low power tests. We have no evidence that sharing the name of a famous author increases or decreases citation rates. Comparing the coefficients on first- and later-authors, one difference out of 10 is significant at the 10% level. Again, we have no evidence that the first author's having a famous last name differentially affects citations relative to the second or third author's having a famous last name.

Table A1: Author fame and paper citation percentile for four-authored papers

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. We include only four-author papers. In each column, fame is defined as the number of papers with citations weakly above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50, 75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	10.265	18.519	28.314	48.454	74.311
	(3.645)	(4.537)	(6.154)	(10.674)	(15.913)
Author 2: Fame	10.020	17.305	27.339	34.631	42.933
	(3.417)	(4.605)	(6.648)	(11.308)	(16.190)
Author 3: Fame	12.536	21.453	32.069	48.425	66.729
	(3.381)	(4.579)	(6.519)	(10.229)	(14.945)
Author 4: Fame	3.943	12.162	18.201	23.686	25.819
	(3.494)	(4.526)	(6.014)	(8.547)	(11.775)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.963	0.861	0.921	0.422	0.215
Author 1 and Author 3	0.653	0.652	0.681	0.999	0.732
Author 1 and Author 4	0.230	0.355	0.279	0.099*	0.026**
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,252	3,252	3,252	3,252	3,252
R-squared	0.413	0.423	0.430	0.429	0.426

Table A2: Author fame and citations per year percentile

The dependent variable in all the specifications is Citations per year percentile, the percentile rank within the entire sample for the citations divided by the number of years since publication of the paper, multiplied by 100. In Panel A and C, we include two-authored papers and in Panel B and D, three-authored papers. In each column, we count the number of papers by each author whose citations are above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50 ,75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations per year percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	17.867	28.491	41.099	62.431	86.743
	(0.632)	(0.846)	(1.240)	(2.355)	(3.924)
Author 2: Fame	14.090	22.939	35.428	56.301	77.863
	(0.566)	(0.776)	(1.177)	(2.099)	(3.328)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.000***	0.000***	0.004***	0.088*	0.124
Journal x Year FE	No	No	No	No	No
Observations	39,046	39,046	39,046	39,046	39,046
R-squared	0.044	0.064	0.071	0.062	0.051

Panel B: Three-author papers

Dependent Variable: Citations per year percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	15.263	24.402	35.727	60.958	92.737
	(1.011)	(1.325)	(1.847)	(3.144)	(4.932)
Author 2: Fame	10.637	18.902	29.833	41.506	53.700
	(1.028)	(1.360)	(1.983)	(3.484)	(5.252)
Author 3: Fame	11.011	18.259	27.708	40.539	52.071
	(1.014)	(1.358)	(1.934)	(3.101)	(4.614)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.002***	0.006***	0.042**	0.000***	0.000***
Author 1 and Author 3	0.006***	0.003***	0.006***	0.000***	0.000***
Journal x Year FE	No	No	No	No	No
Observations	16,920	16,920	16,920	16,920	16,920
R-squared	0.035	0.053	0.063	0.056	0.048

Panel C: Two-author papers

Dependent Variable: Citations per year percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	11.519	19.308	28.314	43.601	60.149
	(0.560)	(0.740)	(1.059)	(1.918)	(3.100)
Author 2: Fame	9.256	15.870	24.351	37.559	51.793
	(0.501)	(0.677)	(1.012)	(1.776)	(2.790)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.005***	0.001***	0.014**	0.036**	0.067*
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39,046	39,046	39,046	39,046	39,046
R-squared	0.393	0.402	0.406	0.403	0.398

Panel D: Three-author papers

Dependent Variable: Citations per year percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	7.716	13.685	21.080	36.170	55.713
	(0.872)	(1.139)	(1.575)	(2.676)	(4.255)
Author 2: Fame	5.229	10.606	18.027	25.687	34.301
	(0.903)	(1.175)	(1.623)	(2.559)	(3.770)
Author 3: Fame	4.163	8.543	13.848	19.821	24.161
	(0.855)	(1.139)	(1.587)	(2.397)	(3.419)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.051*	0.069*	0.197	0.007***	0.000***
Author 1 and Author 3	0.005***	0.002***	0.002***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,920	16,920	16,920	16,920	16,920
R-squared	0.489	0.494	0.498	0.497	0.496

Table A3: Author fame and paper citation percentile for older papers

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. In Panel A, we include two-author papers and in Panel B, three-author papers. Fame is defined as the number of papers with citation percentile weakly above 95. For columns (1), (2), (3), (4) and (5), we include papers which are more than 6, 7, 8, 9, and 10 years since publication respectively. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile	(1)	(2)	(3)	(4)	(5)
Author 1: Fame	61.114	61.158	62.689	63.003	63.277
	(3.213)	(3.279)	(3.324)	(3.382)	(3.470)
Author 2: Fame	52.237	52.029	52.852	52.607	53.118
	(2.939)	(2.989)	(3.051)	(3.087)	(3.148)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.063*	0.065*	0.043**	0.040**	0.050**
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	31,673	30,306	28,949	27,639	26,359
R-squared	0.353	0.355	0.358	0.357	0.357

Panel B: Three-author papers

Dependent Variable: Citations percentile	(1)	(2)	(3)	(4)	(5)
Author 1: Fame	56.212	59.430	61.249	63.001	65.454
	(4.747)	(4.973)	(5.309)	(5.530)	(5.768)
Author 2: Fame	34.574	32.947	32.022	31.977	31.211
	(4.043)	(4.112)	(4.260)	(4.389)	(4.521)
Author 3: Fame	25.112	25.226	25.808	25.777	26.252
	(3.798)	(3.904)	(4.156)	(4.295)	(4.580)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.012**	0.000***	0.000***	0.000***	0.000***
Author 1 and Author 3	0.000***	0.000***	0.000***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	11,357	10,504	9,721	9,004	8,321
R-squared	0.421	0.433	0.439	0.442	0.449

Table A4: Citations percentile within journal-year

The dependent variable in all specifications is Citations percentile in journal-year, the raw citations percentile of the paper amongst all papers published in the same journal and in the same year, multiplied by 100. In Panel A, we include two-authored papers and in Panel B, three-authored papers. In each column, we count the number of papers by each author whose citations are above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50 ,75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile in journal-year	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	20.445	33.987	50.851	79.962	111.744
	(0.861)	(1.149)	(1.654)	(3.040)	(5.044)
Author 2: Fame	15.650	26.945	42.115	66.602	92.224
	(0.779)	(1.066)	(1.607)	(2.937)	(4.693)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.000***	0.000***	0.001***	0.004***	0.010***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39,046	39,046	39,046	39,046	39,046
R-squared	0.104	0.121	0.129	0.125	0.118

Panel B: Three-author papers

Dependent Variable: Citations percentile in journal-year	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	15.762	27.404	42.461	73.710	114.855
	(1.412)	(1.917)	(2.729)	(4.756)	(7.638)
Author 2: Fame	10.865	21.248	35.733	52.017	69.111
	(1.425)	(1.899)	(2.682)	(4.435)	(6.779)
Author 3: Fame	9.269	18.405	30.210	45.913	58.385
	(1.389)	(1.888)	(2.698)	(4.276)	(6.278)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.019**	0.030**	0.099*	0.002***	0.000***
Author 1 and Author 3	0.002***	0.002***	0.003***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,920	16,920	16,920	16,920	16,920
R-squared	0.120	0.136	0.147	0.146	0.143

Table A5: Author fame and paper citation percentile with additional control variables

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. In Panel A, we include two-authored papers and in Panel B, three-authored papers. In each column, fame is defined as the number of papers with citations weakly above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50, 75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	21.723	36.789	52.638	78.519	106.674
	(0.769)	(1.028)	(1.505)	(2.876)	(4.816)
Author 2: Fame	17.366	30.113	45.077	67.660	90.827
	(0.699)	(0.961)	(1.459)	(2.649)	(4.179)
Lead article	531.110	467.925	441.649	462.591	495.582
	(44.325)	(43.922)	(43.721)	(43.822)	(43.949)
Years since publication	59.811	63.445	60.339	52.981	47.935
	(2.006)	(1.958)	(1.927)	(1.918)	(1.924)
Journal Impact Factor	113.110	102.716	98.797	103.189	108.635
	(2.713)	(2.697)	(2.695)	(2.708)	(2.720)
Average age of authors	-43.768	-49.351	-43.143	-31.661	-24.573
	(2.313)	(2.229)	(2.161)	(2.129)	(2.129)
p-value for test of difference in coefficients of Author 1 and Author 2	0.000***	0.000***	0.001***	0.011**	0.021**
Journal x Year FE	No	No	No	No	No
Observations	39,014	39,014	39,014	39,014	39,014
R-squared	0.129	0.152	0.161	0.152	0.142

Panel B: Three-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	18.398	31.892	46.875	77.628	117.553
	(1.226)	(1.657)	(2.345)	(4.035)	(6.414)
Author 2: Fame	11.560	23.832	37.146	49.962	62.423
	(1.232)	(1.655)	(2.506)	(4.433)	(6.648)
Author 3: Fame	12.041	22.617	33.360	45.054	53.838
	(1.209)	(1.654)	(2.416)	(3.907)	(5.616)
Lead article	510.212	441.688	403.664	426.044	451.306
	(66.358)	(65.716)	(65.319)	(65.438)	(65.602)
Years since publication	58.959	64.795	61.420	53.156	47.478
	(3.479)	(3.385)	(3.315)	(3.272)	(3.251)
Journal Impact Factor	126.467	112.329	105.881	110.512	116.846
	(4.106)	(4.121)	(4.124)	(4.118)	(4.100)
Average age of authors	-53.425	-61.679	-54.660	-41.165	-33.462
	(3.974)	(3.792)	(3.630)	(3.524)	(3.485)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.000***	0.001***	0.007***	0.000***	0.000***
Author 1 and Author 3	0.000***	0.000***	0.000***	0.000***	0.000***
Journal x Year FE	No	No	No	No	No
Observations	16,907	16,907	16,907	16,907	16,907
R-squared	0.113	0.136	0.148	0.142	0.134

Table A6: Author fame and paper citation percentile with additional control variables and journal-year fixed effects

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. In Panel A, we include two-authored papers and in Panel B, three-authored papers. In each column, fame is defined as the number of papers with citations weakly above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50, 75, 90, and 95, respectively. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	20.987	33.117	46.380	68.984	93.475
	(0.766)	(1.022)	(1.470)	(2.708)	(4.447)
Author 2: Fame	16.810	27.166	39.604	58.608	78.522
	(0.693)	(0.947)	(1.419)	(2.538)	(3.964)
Lead article	444.786	397.581	377.976	397.341	425.601
	(43.111)	(42.838)	(42.722)	(42.815)	(42.907)
Average age of authors	-40.902	-43.185	-37.166	-27.562	-21.633
	(2.258)	(2.189)	(2.131)	(2.101)	(2.097)
p-value for test of difference in coefficients of Author 1 and Author 2	0.000***	0.000***	0.002***	0.001***	0.020**
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39,014	39,014	39,014	39,014	39,014
R-squared	0.278	0.292	0.296	0.290	0.283

Panel B: Three-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	18.437	29.091	41.374	67.266	100.931
	(1.265)	(1.714)	(2.410)	(4.142)	(6.615)
Author 2: Fame	13.962	23.788	35.227	46.870	59.932
	(1.248)	(1.645)	(2.378)	(3.979)	(5.997)
Author 3: Fame	12.766	21.099	29.749	39.571	46.652
	(1.210)	(1.622)	(2.306)	(3.597)	(5.141)
Lead article	349.462	302.238	275.283	299.428	320.318
	(66.216)	(65.836)	(65.636)	(65.727)	(65.814)
Average age of authors	-57.271	-59.441	-51.794	-40.042	-33.594
	(3.958)	(3.781)	(3.625)	(3.534)	(3.506)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.012**	0.030**	0.083*	0.001***	0.000***
Author 1 and Author 3	0.001***	0.000***	0.001***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,907	16,907	16,907	16,907	16,907
R-squared	0.303	0.316	0.322	0.317	0.312

Table A7: Author fame and paper citations percentile – Dividing journals by impact factor

The dependent variable in all the specifications is citations percentile, the raw citations percentile of the paper multiplied by 100. In Panel A, we include two-authored papers and in Panel B, three-authored papers. Author fame is defined to be her number of papers with citations percentile above 95. In column (1) ((2)) we include journals which have above (below) median SCIMAGO impact factors in the year 2015. In columns (3) ((4)) we include journals which have above (below) median SCIMAGO impact factors in the year 2019. In columns (5) ((6)) we include journals which have above (below) median RePEc impact factors. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile	(1)	(2)	(3)	(4)	(5)	(6)
Author 1: Fame	78.538	127.079	77.714	122.684	84.360	112.260
	(4.760)	(8.883)	(4.772)	(8.448)	(4.764)	(9.318)
Author 2: Fame	70.748	86.732	67.148	95.419	68.640	97.124
	(4.405)	(7.598)	(4.383)	(7.569)	(4.348)	(7.594)
p-value for test of difference in coefficients of						
Author 1 and Author 2	0.274	0.002***	0.138	0.028**	0.027**	0.242
Journal x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,143	20,903	16,102	22,944	22,877	16,169
R-squared	0.231	0.248	0.214	0.236	0.304	0.179

Panel B: Three-author papers

Dependent Variable: Citations percentile	(1)	(2)	(3)	(4)	(5)	(6)
Author 1: Fame	81.508	126.439	76.525	127.012	83.214	126.160
	(7.268)	(13.057)	(7.512)	(11.841)	(7.520)	(12.428)
Author 2: Fame	47.986	86.289	41.129	104.430	47.656	85.384
	(6.154)	(13.130)	(5.794)	(13.063)	(6.033)	(14.401)
Author 3: Fame	37.738	56.226	38.317	57.493	37.680	63.978
	(5.186)	(12.497)	(5.177)	(12.181)	(5.147)	(13.288)
p-value for test of difference in coefficients of						
Author 1 and Author 2	0.001***	0.040**	0.000***	0.233	0.001***	0.039**
Author 1 and Author 3	0.000***	0.000***	0.000***	0.000***	0.000***	0.002***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,374	9,546	6,257	10,663	9,916	7,004
R-squared	0.261	0.264	0.248	0.255	0.335	0.202

Table A8: Author fame and paper citations percentile – Actual author order

The dependent variable in all specifications is Citation percentile, the raw citation percentile of the paper multiplied by 100. In Panel A, we include two-authored papers and in Panel B, three-authored papers. In each column, fame is defined as the number of papers with citations weakly above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50, 75, 90, and 95, respectively. Each author's position is based on the actual author order in the paper. Our sample includes all papers published after the latter of 1974 and the journal's founding. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	16.580	27.956	41.831	65.313	90.165
	(0.736)	(0.985)	(1.434)	(2.638)	(4.332)
Author 2: Fame	13.291	22.715	35.079	54.846	75.918
	(0.662)	(0.906)	(1.357)	(2.434)	(3.836)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.002***	0.000***	0.002***	0.009***	0.025**
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	39,046	39,046	39,046	39,046	39,046
R-squared	0.268	0.282	0.288	0.284	0.278

Panel B: Three-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	13.349	23.141	35.962	62.270	94.318
	(1.207)	(1.635)	(2.332)	(4.070)	(6.516)
Author 2: Fame	8.973	17.803	30.189	43.469	58.192
	(1.230)	(1.628)	(2.308)	(3.859)	(5.884)
Author 3: Fame	6.566	13.584	21.981	32.397	40.098
	(1.182)	(1.586)	(2.233)	(3.425)	(4.937)
p-value for test of difference in coefficients of					
Author 1 and Author 2	0.015**	0.028**	0.097*	0.002***	0.000***
Author 1 and Author 3	0.000***	0.000***	0.000***	0.000***	0.000***
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,920	16,920	16,920	16,920	16,920
R-squared	0.291	0.302	0.311	0.309	0.306

Table A9: Author fame and paper citations percentile – Other famous authors with same last name

The dependent variable in all specifications is Citations percentile, the raw citations percentile of the paper multiplied by 100. In Panel A, we include two-authored papers and in Panel B, three-authored papers. In each column, fame is defined as the number of papers by each author whose citations are above the Xth percentile. For columns (1), (2), (3), (4) and (5), X is equal to 0, 50 ,75, 90, and 95, respectively. The variable Superstar author with same last name as Author 1 (2 or 3) takes the value one if there exists a superstar author with the same last name as Author 1 (2 or 3) and zero otherwise. Our sample includes all papers published after the latter of 1974 and the journal's founding with no superstar authors. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively resulting from F-tests for the linear restriction to equality of coefficients.

Panel A: Two-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	13.384	32.433	63.719	140.809	252.170
	(1.029)	(1.577)	(2.599)	(5.663)	(10.819)
Author 2: Fame	11.707	27.361	55.184	124.062	226.890
	(0.914)	(1.394)	(2.402)	(5.412)	(10.424)
Superstar author with same last name as Author 1	-56.776	-57.489	-53.646	-64.194	-90.979
	(69.613)	(69.057)	(68.523)	(68.316)	(68.198)
Superstar author with same last name as Author 2	-65.155	-72.202	-61.309	-55.334	-67.665
	(59.172)	(58.601)	(58.126)	(57.814)	(57.731)
p-value for test of difference in coefficients of Famous author with same last name as Author 1 and Author 2	0.927	0.872	0.932	0.922	0.795
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,915	34,915	34,915	34,915	34,915
R-squared	0.244	0.257	0.267	0.269	0.265

Panel B: Three-author papers

Dependent Variable: Citations percentile	(1) X=0	(2) X=50	(3) X=75	(4) X=90	(5) X=95
Author 1: Fame	8.151	21.588	44.311	102.324	200.341
	(1.734)	(2.646)	(4.299)	(9.359)	(17.845)
Author 2: Fame	4.759	15.478	40.306	93.490	177.603
	(1.618)	(2.544)	(4.321)	(9.199)	(17.509)
Author 3: Fame	6.522	18.789	43.426	102.390	180.698
	(1.586)	(2.451)	(4.162)	(8.975)	(17.246)
Superstar author with same last name as Author 1	64.155	58.505	63.797	57.962	71.684
	(117.909)	(116.509)	(115.145)	(114.520)	(115.430)
Superstar author with same last name as Author 2	-106.757	-127.231	-134.839	-133.987	-127.106
	(103.242)	(102.742)	(102.104)	(101.589)	(101.218)
Superstar author with same last name as Author 3	-147.818	-177.919	-193.732	-153.712	-129.148
	(95.684)	(94.892)	(94.140)	(93.780)	(94.301)
p-value for test of difference in coefficients of					
Famous author with same last name as Author 1 and Author 2	0.282	0.238	0.203	0.216	0.202
Famous author with same last name as Author 1 and Author 3	0.164	0.117	0.085*	0.155	0.178
Journal x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	14,900	14,900	14,900	14,900	14,900