The Reverse Matthew Effect: Consequences of Retraction in Scientific Teams*

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Abstract

Teamwork pervades modern production and organizations, yet teamwork can make individual roles difficult to ascertain. In assigning individual rewards, the "Matthew Effect" suggests that communities presume eminent team members are responsible for great outcomes, reducing the credit that accrues to less eminent team members. We study this phenomenon in reverse, investigating credit sharing for damaging events. Our empirical context is article retractions in the sciences and the effect these negative events impose on citations to the authors' prior work. We find that retractions impose little citation penalty on eminent coauthors, but less eminent coauthors face substantial citation declines, especially when teamed with an eminent author. These findings suggest a "Reverse Matthew Effect" for team-produced negative events. A Bayesian model provides a candidate interpretation.

Keywords: teamwork, reward, reputation, information, science, retraction, Matthew Effect.

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1. Introduction

Teamwork is pervasive in modern production contexts, with benefits often related to the division of labor in executing tasks and/or creative advantages in driving innovation.[1] Yet team production raises challenges, including challenges in finding appropriate reward structures for team participants. Indeed, in many team production contexts, the joint output is observable but the separate inputs of individual team members are difficult to discern, which makes the assignment of credit difficult.[2] In situations where the output of the individual is not directly observed, reputation may become a cornerstone not only in providing effort incentives but also in shaping how outsiders assign credit within a team.

In a classic study, Robert K. Merton suggested the "Matthew Effect" as a fundamental issue in an important team production context, science (Merton 1968). Like many team production contexts, science is a setting where the joint output of the team is observable but the individual contributions of the team members are less clear. Merton argued that, in this setting, more eminent team members tend to limit the credit received by less eminent team members.[3] In Merton's analysis, the community, upon witnessing a great contribution, assumes that the already eminent team member was the key producer while less well-known team member(s) were less important contributors who deserve less credit. However, empirical evidence on the foundational question of how credit is shared across team members remains limited.

Using scientific publications as an example, this paper considers a natural experiment to assess the individual consequences of working in teams. Our question, however, concerns not the rewards of "good" events, but rather the consequences of "bad" events. Namely, we look at the

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[1] See, e.g., classic observations in Bacon (1620) and Smith (1776) or modern analyses such as Becker and Murphy (1992), Woodman et al. (1993), Jones (2009), and the broader literature discussed in Section 2.

[2] See, e.g., Holmstrom (1982), Welbourne et al. (1995), Wageman and Baker (1997), Bikard et al. (2015), and the large literature discussed in Section 2.

[3] Merton coined the Matthew Effect after the biblical passage "For unto every one that hath shall be given, and he shall have abundance: but from him that hath not shall be taken even that which he hath" (Matthew 25: 29, King James Version).

effect of article retractions in team production settings and examine whether eminent team members attract or repel blame compared to less eminent team members. On the one hand, one might imagine that eminent individuals receive disproportionate credit for the joint output, whether good or bad, as the presumed leader of the enterprise. On the other hand, one may imagine that eminent individuals have such established reputations that they escape blame for bad events, leaving any blame to accrue to junior team members. Thus we may imagine a "Reverse Matthew Effect" through which less eminent team members experience greater, negative consequences.

In our empirical analysis, we collect retracted articles in the Web of Science where the retracted paper was authored in a team and where the authors have a single retraction event.[4] We then investigate citations to the prior publications of each author involved in the retracted work. To examine the effect of retraction, we match each of these prior publications (the treated papers) with a set of other publications (the control papers) that were published in the same field-year and received similar citations every year before the retraction event. This approach allows us to identify the effect of retraction via difference-in-differences estimation. This identification strategy builds from the observation that the content of prior work is unchanged, so that changes in citations to this work, compared to counterfactual control papers, reveal the effect of the retraction shock.[5]

Using standard measures of eminence, we find four central results following retraction events. First, less established team members experience substantial citation declines to their prior work. Second, by contrast, eminent team members experience little or no citation consequences

[4] That is, in our main analysis, we do not look at extreme cases where an author is revealed to be a systematic fraud as such cases make the credit assignment problem straightforward. We will, however, also consider the multiple retraction cases as a falsification exercise and show that, as expected when the guilty party is obvious, prior reputation no longer matters.
[5] Using citations to prior scientific work to assess the effects of shocks was pioneered as an identification strategy in Furman and Stern (2011).

for their prior work. Third, less established team members are especially negatively affected in the presence of an eminent team member. This interaction effect suggests that eminence may act not only to protect oneself, but also to hurt others on one's production team. Fourth, and related, we find that while the citation losses experienced by ordinary team members are exacerbated by the presence of eminent team members, these citation losses are attenuated in the presence of "rookies" – coauthors who had no prior work and are yet more junior to the ordinary coauthor. These results persist across a variety of robustness checks. These findings, where the already "rich" have an advantage over the relatively "poor" in the context of negative events, and where the effects on ordinary individuals depend on the standing of other team members, provide the paper's central results.

Given these findings, and building from reasoning in Merton's original Matthew Effect paper (Merton 1968), we further present a simple Bayesian model as a candidate explanation for the empirical results. In the model, the community attempts to infer each individual's tendency to produce bad output given different priors about each individual and the possibility that anyone might make a mistake. Eminence is defined as a prior reputational state featuring precise beliefs that an individual is a high quality type. When bad output is revealed, the model shows that (1) being eminent helps you; (2) the presence of a more eminent team member hurts you but the presence of a less eminent team member helps you; and (3) eminent teammates hurt you less when you yourself are eminent. The empirical results thus appear broadly consistent with a Bayesian inference problem, where the community assigns blame given priors over the individuals involved and their interactions. While simple, the model captures the suite of empirical findings in an intuitive manner and identifies key primitives that may extend to a broad set of teamwork settings.

2. Literature and Context

Teamwork is a ubiquitous feature of modern production and organizations, where collaborative work is seen from assembly lines to entrepreneurial teams to surgical suites and appears across industrial, agricultural, and service sectors (e.g., Cohen and Bailey 1997, Wuchty et al. 2007). Yet teamwork raises challenges, including challenges in finding appropriate reward structures (e.g., Holmstrom 1982, Welbourne et al. 1995; Wageman and Baker 1997; Bikard et al. 2015). When individuals join together in production, it can be difficult for outsiders to discern the separate inputs of individual team members. This information gap can undermine an organization or community's capacity to reward team members appropriately (e.g., Holmstrom 1982) and can lead outsiders to rely on additional sources of information in making inferences, including the existing reputations of the parties involved (e.g., Merton 1968).

Indeed, information challenges may be overcome through reputation and learning in many contexts, as suggested by large theoretical and empirical literatures.[6] Merton's "Matthew Effect" provides a canonical analysis (Merton 1968). On the one hand, the presence of a team member with a strongly positive reputation can enhance demand for the product (a research article in Merton's setting, where an eminent author attracts greater attention to the output) thus creating a positive spillover on other team members by elevating attention to their work. On the other hand, and according to Merton's primary analysis, the presence of an eminent team member may limit credit for others as the community infers that the eminent team member is more responsible for the output. Thus, while partnering with a high-reputation teammate may enhance demand for the given output, it may also make it difficult for the less-established teammate to become substantially rewarded herself. Such a credit allocation effect, should it be operating, may in turn

[6] The role of reputation in the context of information problems has been emphasized in economics, sociology, and management literatures, with classic analyses including Shapiro (1983) and Rao (1994).

create additional challenges in team production settings. Indeed, credit allocation is the fundamental consideration in classic theories of teamwork and organizations (e.g., Holmstrom 1982, Aghion and Tirole 1994) and may also impact career progress, for example, if young team members struggle to garner credit for their efforts, their interest in the career itself may dim (Stephan 2012, Jones 2010).[7] Understanding reward systems in team production thus appears as a key for understanding team function, team assembly, and career choice, and hence appears as a potentially critical issue for modern management and the economy at large given the prevalence of teamwork today.

Recent literature has examined the reputation effect specifically in the setting of science. Simcoe and Waguespack (2011) show that attention to proposed Internet standards increases substantially when the presence of an eminent author's name is revealed as opposed to hidden. Azoulay et al. (2013) show that citations increase to a researcher's prior body of work after the researcher becomes a Howard Hughes Medical Investigator, a high-status award in the biomedical sciences. Both studies indicate that positive reputational shocks can improve community awareness or perceptions of existing output. By contrast, Lu et al., (2013) and Azoulay et al. (2015) study negative reputational shocks in science, demonstrating penalties from retraction. Azoulay et al. (2017) show that retraction penalties differ by author standing across different retractions.

This paper departs from prior literature by focusing on credit allocation *within teams*. Namely, we examine the allocation of retraction penalties among team members when individual inputs to a team-produced retraction appear unobservable to outsiders. The setting of team science allows us to examine not just how established reputations influence community use, but

[7] For example, the increasing age at which biomedical researchers achieve their first NIH grant is well known and may follow in part from the increasing prevalence of teamwork in research and innovation that makes it difficult for young scholars to establish independent reputations, creating increasing challenges to the career prospects of the young (Stephan 2012, Jones 2010).

how differential reputations *within* a team influence individual-specific consequences. We thus embrace the centerpiece of Merton's seminal analysis, examining the role of an individual's prior reputation and the potential entanglement of reputations in assigning rewards within teams. The communication hypothesis, normally an advantage, suggests that eminence may attract extra attention to the negative event and thus amplify consequences for the individuals involved. The credit hypothesis suggests two distinct alternatives. On the one hand, a strong reputation may protect an individual in case of falsehood, where the community infers that a less-established team member was responsible for the problem. Thus the Matthew Effect may also work in reverse, with eminence not only attracting good credit but also deflecting bad credit. On the other hand, the credit hypothesis may suggest that the community sees the eminent individual as being "in charge" and directing events, in which case the eminent individual may take the blame for mistakes, just as they get credit for successes. Other mechanisms may also bear on community reactions.[8]

Given a rich set of plausible mechanisms, we treat our analysis primarily as an empirical question and seek to establish first-order facts. Having presented these facts, we then return to theory in Section 5 and provide a simple Bayesian interpretation that emphasizes the credit-inference aspects of the problem. This theoretical approach shows how strong prior beliefs can both insulate one's own reputation and deflect consequence onto others.

Azoulay et al. (2017), in a related contribution, find that eminent scientists can be especially harshly penalized in the wake of a retraction in cases involving fraud or misconduct. The sentiment of their empirical results differ from ours, a difference that can be attributed to

[8] For example, team leaders may actively accept or deflect blame, and communities may follow norms in whether they choose to blame leaders. Across various organizational settings one can find anecdotes of leaders who are fired for failures that occur under the "leader's watch", and contrasting examples where leaders appear to scapegoat underlings. In Section 5, we will define key primitives for contexts that can result in Matthew Effects.

distinctions in the research question, sample composition, and empirical approach. In term of the research question, Azoulay et al (2017) compare retraction penalties across different retraction events. They use all retraction cases including solo-authored retractions and multiple retractions from the same author. In doing so, they largely focus on one author per retraction (the principal investigator) and therefore examine variation by author standing *between* teams and *between* retractions. Their context is one where the blameworthy party it typically obvious and where eminent authors have more reputation to lose in the severe case of misconduct. In contrast, we address a team production issue *within the same retraction*, i.e. whether eminent team members receive more or less blame than their less eminent teammates, and further focus on cases where individual responsibility is unclear. Hence, we focus on *within-team* variation and study single retraction cases, for which the information uncertainty about who to blame is substantial. We will discuss these distinctions further below when we present our data, sample and empirical approach.

3. Data and Empirical Framework

Our data comes from the largest known repository of scientific knowledge, the Web of Science (WOS) from Thomson Reuters, which now includes more than 32 million research articles published in over 15,000 journals worldwide, beginning in 1945. This database includes detailed bibliographic information for each paper (authors, journal, publication year, etc.) and further defines the citation linkages between each paper. The WOS further includes retraction notices, and these notices describe the time and reasons for each retraction and whether the errors are reported by the authors.

3.1. Treated Papers

In our study, we focus on changes in citations to an author's *prior published work*. We focus on prior work, i.e., papers published before the retraction event, because this work is in a fixed published form, allowing us to isolate changes in usage of this work from changes in the work itself. Moreover, focusing on prior published work allows us to construct counterfactual cases by matching the prior work to other papers in the WOS that followed very similar citation profiles prior to the retraction event. We refer to each prior publication by authors involved in the retraction as a treated paper.

To build the sample of prior works, we confront a typical challenge in the WOS, where neither author names nor affiliations are uniquely identifiable. For example, many different authors may share the same name. Relying on the name alone would then lead to the inclusion of work not written by that author. To address this, we track the publication history of an author via her self-citation network, assuming that researchers tend to cite their own works in the same field.

In our primary sample and analysis, we focus on "single" retraction events, where the authors for a given team-produced retraction are involved in only one retraction between 1993 and 2009. These cases present the community with an inference challenge in determining who is to blame within the team, raising the possibility of Matthew Effect like outcomes. By contrast, authors with multiple retractions represent the (more extreme) cases where a common author is revealed to have produced many false works, which makes the inference challenge for the community straightforward.[9] We will consider these more extreme cases of multiple retractions, where the blameworthy party becomes obvious, as a falsification test in Section 5.

The retraction notices published in the WOS indicate whether the errors were reported by the authors themselves or not. This allows us to classify retraction cases into self-reported and

[9] Similarly, there is no information uncertainty for solo-authored retractions and those cases do not fit in our focus on teamwork.

non-self-reported retractions.[10] Lu et al. (2013) show that retractions trigger citation losses to an author's prior work but these penalties disappear if the author(s) self-report the error.[11,12] Therefore, to examine how retraction affects authors by differential eminence, our retraction sample focuses on cases where retractions were not self-reported.

In the sample period we located 513 singular retraction events and 95% of these retracted papers (489) were written by more than one author. Among these team-authored retractions, 57.3% (280) were not self-reported, 32.3% (158) were self-reported, and 10.4% (51) had unclear or unknown retraction reasons. For our main retraction sample, we identified each authors' prior work published before the retraction. Changes in citations to these papers are the objects of our empirical analysis. The procedure for identifying prior work of an author, which is based on their citation network, is described in the Online Appendix.

3.2 Control Papers

Because citation patterns differ across disciplines and by time since publication, we construct a control group to match each "treated" paper in the pre-retraction period. The underlying assumption is that both treated and control articles will continue the same course of citation patterns if there were no retraction influencing the treated paper. This methodology draws on an identification approach first used in the context of scientific outputs by Furman and Stern (2011).

[10] The distinction based on self-reporting provides a simple basis for categorization that is reported by the journal. More generally, there are many underlying problems that can lead to retraction, including author error, failure to replicate, data fabrication, and plagiarism, among others. Categorizations along these lines are more challenging to determine from the available commentary about the paper because retractions reasons are often not clearly reported, not mutually exclusive, and often not agreed upon (including by the authors themselves). See further discussion in Lu et al. (2013).

[11] The absence of citation losses with self-reported retractions may indicate that the community interprets these events as innocent mistakes, and/or there may be some offsetting advantage through self-reporting in signaling the authors' trustworthiness. See Lu et al. (2013).

[12] The lack of an overall penalty in self-reported retractions is, not surprisingly, further reflected in the absence of differential penalties across team members in these retractions. These results are available from the authors upon request.

For a treated paper *i* published in field *f* and year *p*, we search for control papers within the same field and the same publication year. Using the WOS, we are able to search across millions of papers to find controls that are minimally distant within the same field, where field is defined by the 252 field categories that WOS uses to classify thousands of journals. In particular, for each non-treated paper *j* in this pool, we define the arithmetic distance between *i* and *j* as

$$\mathrm{AD_{ij}} = \sum_{t=p}^{r-1} (c_{it} - c_{jt}) \tag{1}$$

and the Euclidean distance between *i* and *j* as:

$$\mathrm{ED_{ij}} = \left[\sum_{t=p}^{r-1} \left(c_{it} - c_{jt} \right)^2 \right]^{1/2} \tag{2}$$

where c_{it} denotes the citations paper *i* receives in year *t* and *r* is the year of retraction. Both distances attempt to measure the citation discrepancy between paper *i* and paper *j*, but arithmetic distance $\mathrm{AD_{ij}}$ allows for positive and negative differences to offset each other while Euclidean distance $\mathrm{ED_{ij}}$ is direction free.

The quality of control group matching is assessed in Figure A1 of the online appendix. Because we access the entire WOS, we can find substantially closer controls than is normally the case in other empirical applications of this treatment-control methodology (Furman and Stern 2011; Furman et al. 2012; Azoulay et al. 2017). For example, focusing on the ten papers with the lowest Euclidean distance to a treated paper, the upper-left panel of Figure A1 shows that the average Euclidean distance between the ten controls and the treated paper has high density around zero. The density drops smoothly at higher distances except for the bin of 50 or more (which is driven by some treated papers that were exceptionally highly cited before retraction).[13]

[13] As discussed below, our analysis is driven by cases with close matches and thus does not include such outliers.

As shown in the bottom-left panel of Figure A1, the average arithmetic distance between these ten controls and the treated paper has substantially more density on the negative side, so that these controls on average underestimate the citation flow of the treated papers. Focusing instead on the single control paper with the lowest Euclidean distance, we are able to find a perfect match for 36.1% of the treated papers. When we cannot find a perfect match, the arithmetic distance of the single best control is negative on average, though it is more evenly distributed on both sides of zero than the ten-control sample.

To achieve a sample that balances close matches with sample size, we consider the two nearest neighbors, one from above (with positive AD) and one from below (with negative AD). As shown in the bottom-right panel of Figure A1, the density of the average arithmetic distance of these two controls is either exactly zero or concentrated in the neighborhood of zero. In particular, the two nearest neighbors yield an average of zero arithmetic distance for a large share (68.5%) of our treated papers. This sample, with zero distance, is the main sample used in our analysis. In practice, we have 276 retraction events where authors have closely-matched prior work.[14]

Our control approach is novel to the economics of science literature. Compared to the traditional control approach that attempts to match papers within the same journal and year (Azoulay et al, 2017), our method uses a larger pool of candidate control papers and enables us to find matches with an average of zero arithmetic distance on pre-retraction citation counts.

Overall, by focusing on these 276 team-authored, single retraction events that were not self-reported, our sample includes 732 authors.[15] The mean number of prior publications for

[14] Recall that there are 280 retraction cases of team-authored, single retractions where the authors do not self-report the error, thus we lose four events by focusing on prior publications that have close control matches prior the retraction event.

[15] Note that our main analysis does not include the small number of authors who have multiple retractions (usually, very many retractions). Instead, we uses these cases as a falsification exercise as discussed in Section 5.

these authors is 24.5. The mean number of prior publications for these authors where the two nearest-neighbor controls have zero average arithmetic distance is 16.8 giving a main treatment sample of 12,290 prior publications. This sample, with each treatment paper and its two controls, includes 419,239 paper-year observations. Note that some prior publications will be counted more than once if multiple authors in the sample collaborated on them.[16]

3.3 Definitions of Author Eminence

We construct three standard measures for an author's eminence: publication counts, total citations received, and the h-index. The h-index (Hirsch 2005) attempts to account for publication quantity and quality in a single measure: the number h is the largest scalar for a given scholar such that the scholar has published h papers each of which has been cited at least h times. These measures, which are commonly used as indications of eminence in the scientific community, are calculated using the papers and citations within the WOS. They are calculated for each author in the year just prior to the retraction event.

Taking each treated author as an observation, Figure A2 plots the distribution of the h-index at the time of retraction. Consistent with the previous literature, the distribution is positively skewed, with a long right tail (MacRoberts and MacRoberts 1989, Selgen 1992). Similar skewness exists for paper counts and total citations. In the main part of our statistical analysis, we define the "absolute eminence" of an author using the continuous measures of paper counts, total citations, or h-index. As alternative measures, we also define simple dummy variables to indicate whether an author is in the top 10th percentile of the eminence measure.[17]

[16] In practice, the estimation sample of 12,290 prior publications from retraction authors is constituted by 10,209 unique prior publications, some of which are shared by multiple authors. We cluster standard errors by the retraction event (i.e. the 276 cases) to allow for correlated shocks across the prior work within a given author and across authors involved in the same retraction event.
[17] In robustness tests, we have alternatively defined eminent authors by the top 5% instead of the top 10%. Results are similar.

Because we focus on retractions of team-authored papers, we also define relative measures of social standing based on whether an author has the highest or second highest standing in the team at the time of retraction. These authors are referred to as "relatively eminent." Compared to the absolute measure of author eminence, relative eminence helps us examine differential standings within a team, even if all team members have high or low eminence metrics in absolute terms. The relative eminence measure can also help filter out heterogeneity in the absolute measures across different academic fields.

3.4 Summary Statistics

Table 1 provides two panels of summary statistics: Panel A, at the author level, considers the standing of each treated author at the time of retraction; Panel B, at the paper level, considers summary statistics for the retracted papers and prior work. Panel A shows that authors of a retracted paper had, at the time of retraction, a mean of 24 prior publications, 1,071 citations, and an h-index of 10. Whether measured by total counts of prior work, total counts of citation, or h-index, these author measures appear dispersed and right-skewed. Defining eminence by whether an author's prior-retraction h-index is among the top 10 percentile, Panel A shows that eminent authors have much more publications, receive much more citations, and have been publishing over a greater number of years than ordinary authors.

The retracted papers have 5.9 authors per paper on average (Panel B). Among the prior publications of these authors, 45.5% were published in the 2000s, 40.0% were published in the 1990s, and 14.5% were published in the 1980s. The mean yearly citation count for the prior publications is 3.0. With our sample ending in 2009, the mean age of a prior publication in 2009 is 11.6 years. The mean age of an author's prior publications in the year that author experiences a retraction is 8.5 years.[18]

3.5 Estimation Equation

Our identification strategy employs difference-in-differences. We examine the citation effects of retraction shocks comparing the pre-post differences for treatment papers with the pre-post differences for control papers, while further comparing these differences across authors with different standings. The regression model is

$$\begin{gathered}\Pr(y_{iat}) = f(\alpha_{ia} + \mu_t + \beta_1 \cdot Treat_i \cdot Post_{kt} + \beta_2 \cdot Standing_a \cdot Treat_i \cdot Post_{kt} + \\ \beta_3 \cdot Standing_a \cdot Post_{kt} + \beta_4 \cdot Post_{kt})\end{gathered} \tag{3}$$

where i indexes article, a indexes author, t indexes year since publication, and k indicates a treatment-control paper group. The dependent variable, y, denotes counts of citations to article i at time t for author a. Fixed effects for each paper and author with a retraction (α_{ia}) and each year since publication (μ_t) capture the mean citation pattern of articles. $Treat_i$ is a dummy variable that equals 1 if article i is a treatment paper, and $Post_{kt}$ is a dummy variable that equals 1 if year t is after the retraction event for a given treatment and control group k. $Standing_a$ measures the eminence of the treated author in the year prior to the retraction.[19] For clarity in interpretation, we normalize $Standing_a$ as a z-score, so that $Standing_a = 0$ corresponds to the average treated author and $Standing_a = 1$ indicates an author one standard deviation above the mean. For the three standing measures, the means and standard deviations are given in Table 1.

The coefficient β_1 captures the effect of the retraction shock on citations to prior work of ordinary authors, compared to closely-matched control papers. The coefficient β_2 captures any

[18] With the rapid increase in retraction rates over the last decade (Fang et al. 2012, Lu et al. 2013), most retraction events provide a relatively brief window ex-post to observe ongoing citation behavior; thus, the regression analysis is primarily driven by citation responses to retraction events in the initial few years. We will explore effects on both recent and older publications below.

[19] Note that the interaction term $Standing_a$*$Treat_i$ is absorbed by the paper-author fixed effect (α_{ia}).

difference in the effect on authors with an eminence measure one standard deviation above that of the average treated author. We estimate (3) using the standard Poisson model for count data. While there are 10,209 unique prior publications in the treated sample, to be conservative we cluster the standard errors by the retraction event, giving 276 paper groups.[20]

The key identification assumption is that the prior work would continue the same course of citations as its control papers had the retraction not occurred.[21] Later, we will present a placebo test to further support this assumption. To the extent that this assumption may be less valid if the prior work is published close to the retraction time and therefore provides a shorter time window for matching control papers, we will also later exclude such cases as a robustness check.

4. Results

As a first look at the raw data, Figure A3 shows the citation flows to prior publications before and after retraction, separating the data by author standing. On the horizontal axis, zero demarcates the year of retraction. The solid blue line shows treated papers, and the dashed red line shows control papers. In the upper row we separate out the author with the greatest h-index on the team (left panel) from the other team members (right panel). The bottom row distinguishes the top two highest h-index authors from the other authors of the retracted paper.

These graphs suggest that the post-retraction citation decline is noticeably negative for more ordinary authors, while relatively eminent authors experience no citation loss. These pictures of the raw data group papers from fields with different citation dynamics and also group

[20] This approach allows arbitrary correlations in the errors across time for a given treated paper, across treated papers by the same author, and across all treated papers by distinct authors who were later involved in the same retraction event. A less conservative approach clusters papers based on the prior publication treatment-control group. Statistical precision with this latter approach is, not surprisingly, greater; these results are discussed briefly in Section 4.2.3 below.

[21] Note that conceivably the retraction event could slow progress of the field, which might cause a decrease in citations to the control papers. Such an effect would lead to a conservative bias in assessing the overall citation loss to the prior work. Note also, however, that our emphasis is on the differential effect between authors based on their reputation; any contamination on control papers would then be differenced out if such contamination is similar for eminent and ordinary authors.

papers with different lengths of observed citation histories.[22] The rest of this section analyzes the data using regression models, presents our central findings, and considers robustness checks.

4.1 Main Results

Pooling the data across authors in our sample, we first confirm that retraction has a significant negative spillover effect on citations to the authors' prior work. The regression results are presented in Figure 1, drawing on the approach of Lu et al. (2013).[23] Compared to the control papers, the annual flow of citations to prior publications falls 4.8% ($p<.0001$) in the first two years post retraction and 13.0% ($p<0.0001$) five or more years post retraction. This suggests that retractions lead to substantial citation declines to prior work in team-authored papers, which is consistent with the results shown in Lu et al. (2013) for retracted papers more generally.

4.1.1 Absolute Standing

Table 2 reports results from our main specification. We highlight the difference-in-differences coefficient on *Treated * Post (t>=1)* retraction and the relative effect on individuals with greater standing from the coefficient on *Standing * Treated * Post (t>=1).*[24] The latter indicates whether a treated author with greater absolute standing at the time of retraction experiences different citation consequences for their prior work. There are three columns in the table, differing by measures of eminence, using total prior publications, total prior citations, and the h-index respectively.

All measures show that the main effect (for those with the mean absolute standing measure) is negative and statistically significant. Meanwhile, the three continuous measures

[22] In Figure 1, retraction events are seen to occur near the paper's peak citation rate on average. This timing tendency is related to fact that papers tend to be retracted when they are highly cited – i.e. when they are receiving attention (Lu et al. 2013). Note also that the citation fluctuations in the post-retraction period are due to sample attrition given different lengths of observable post-periods between the retraction year and the end of our sample period. The fact that the control papers show similar dynamics to the treated papers, including in peak timing, indicates the quality of the match.

[23] This graph differs slightly from the analysis in Lu et al. (2013) because, here, we are interested in and present team-authored cases, where Matthew Effect like outcomes may emerge.

[24] We separate out the retraction year itself (t=0) because the exact time of retraction could occur early or late within the year.

show that higher absolute standing offsets the negative main effect, with statistically significant interactions when using total prior citations or the h-index. Broadly, the coefficients are of similar magnitude across the three measures. Focusing on column (3), a retraction leads to a 10.8 percentage point decline in yearly citations to prior work for an average author. This main effect is offset by a 2.9 percentage point smaller decline in citations per one standard deviation increase in absolute eminence.[25] This finding suggests that having higher standing at the time of retraction may help alleviate the reputational harm due to retraction. Being more eminent suggests a protective effect. Figure 2A repeats the analysis of Figure 1 but now observing how the citation losses to prior work differ between eminent and non-eminent authors.[26] Eminent authors are defined as those with an h-index in the upper 10th percentile, while other authors are classified as non-eminent. Commensurate with Table 2 and Figure 1, we see large citation declines to the prior work of non-eminent authors and this decline increases with time after the retraction. By contrast, eminent authors see modest if any decline in citations to their prior work.

4.1.2 Standing Relative to Coauthors

Beyond one's own absolute standing, we further consider the implications of coauthors' relative standing, as emphasized by Merton (1968). To capture relative standing within the team, we separate out those authors who have the highest standing on the team, even if they don't have high standing in an absolute sense. In particular, we define a dummy equal to one if a treated author has the highest measured standing or, separately, if the author is among the two individuals on the team with the greatest standing. As before, author standing is measured in the

[25] Because the estimation is done in a Poisson model, the marginal effect (in percent) of a one-unit change in a variable is exp(coefficient)-1. In column 3 of Table 2, exp(-0.114)-1=0.108 and exp(-0.029)-1=0.0294.

[26] The econometric specification is the same as In Table 2, only we break up the Post period into several periods, as indicated in the figure; namely, the regression includes separate post period dummies for 1-2, 3-4, and 5+ years after the retraction event.

year prior to the retraction and is alternatively defined using the total number of prior publications, the total citations received, and the h-index.

Table 3 reports the results. As before, the main effect for those with low relative standing is negative and statistically significant across all specifications. When looking at the highest standing author (Columns 1-3), we consistently see large, offsetting positive point estimates, which are significant at the 10% level when using the total number of prior citations or the h-index.[27] When looking at the two authors with highest relative standing (Columns 4-6),[28] we see larger point estimates and greater statistical significance across the measures. Moreover, the estimates for relatively low-standing authors become increasingly negative, suggesting that looking at the top two individuals may more neatly divide high and low standing individuals within the typical team.

Figure 2B repeats the analysis of Figure 2A but now using relative standing, where the relatively eminent authors are defined as the top team member by h-index, while the relatively non-eminent authors are the other team members. We again see large citation declines to the prior work of non-eminent authors, and larger declines with time after the retraction. By contrast, the most eminent team member sees modest if any decline in citations to his or her prior work.

4.1.3 Team Configuration

A further set of tests generalizes the empirical model (3) to consider more textured team configurations. In particular, using binary absolute eminence measures (the top 10 percentile as the cutoff), we can consider the effects of retraction given four different configurations among the authors of the retracted paper. These regressions include dummy variables to indicate

[27] These results strengthen when looking at alternative specifications in Section 4.2.
[28] Recall that our sample includes only team-authored retracted papers. Among the retracted papers, 93% have three or more authors. To keep the sample identical across analyses, we continue to include the 7% of retracted papers with two-authors in columns (4)-(6). Limiting the sample to retracted papers with three or more authors produces virtually identical results in magnitude and statistical significance. Results are available upon request.

whether (i) one's own standing is ordinary and the highest-standing coauthor is ordinary, (ii) one's own standing is ordinary but a coauthor is eminent, (iii) one's own standing is eminent and the highest-standing coauthor is ordinary, and (iv) one's own standing and a coauthor are both eminent (the omitted category in the regression). Here, the coauthor refers to the best coauthor in a team. The results are presented in Table 4, columns (1)-(3), with each column using a different measure of standing: total publications, total citations, and the h-index.

We see that the spillover effect on prior work is most negative when one has ordinary standing and is in the presence of an eminent coauthor. This finding generalizes across the standing measures with varying statistical significance. Taking column (3), for the h-index, the loss on prior work is 15.2% larger when you are ordinary and your coauthor is eminent, compared to the baseline where you were also eminent yourself. Indeed, being eminent yourself suggests little citation losses to your prior work and regardless of the standing of your coauthors, which is seen both in the main effect (you and a coauthor are eminent) and in the interaction effect where you are eminent and your highest standing coauthor is not.

The above approach considers an author's own standing and its interaction with the highest standing coauthor. While simple and transparent, other approaches may be additionally informative as team configurations can be more complex. In particular, teams typically contain "rookie" coauthors, i.e. those with no prior publication history in our data. As the least established members of the team, the presence of these individuals may play important roles in modulating the effect of retractions on the other coauthors.

Table 5 presents additional analyses to look at the presence of rookie coauthors. Focusing on the h-index, the first column repeats our basic analysis in Table 2 column 3 but now adds team size fixed effects and the percentage of rookie coauthors on the retracted paper.[29] The earlier findings regarding author standing are robust, where the average author experiences large citation losses to their prior work while being more eminent tends to limit these citation losses. The new finding is that the presence of rookie coauthors tends to limit substantially the citation losses for the other authors. The second and third columns of Table 5 further examine the role of rookie coauthors for eminent and ordinary authors separately. Here we see that the presence of rookie coauthors has a weak effect for the eminent (who already experience little citation loss) but can substantially offset the losses for ordinary authors. For ordinary authors, moving from no rookie coauthors to all rookie coauthors offsets 88% of the citation losses.

Taken together, Tables 2 through 5 show a consistent pattern. After retraction, the average author experiences large citation losses to their prior work. The citation loss for ordinary authors is amplified when working with an eminent coauthor and attenuated when working with rookie coauthors. Eminent authors, meanwhile, show little citation losses to their prior work, regardless of the standing of their coauthors. A variety of additional tests discussed below further support these results and tend to strengthen their magnitudes or statistical precision.

4.2 Additional Tests and Robustness Checks

We consider here several additional tests to explore the robustness of the above results and further sharpen the empirical findings. These analyses are presented in Tables A1, A2 and A3, which further investigate the main results in Section 4.1 but with changes to the sample or econometric specification. Table A1 repeats the analysis of Table 3, focusing on relative standing in the team to see if relatively ordinary authors continue to experience large citation losses to their prior work while the relatively eminent authors experience smaller losses. Tables

[29] The team size fixed effects are interacted with the treatment and post dummies; the inclusion or exclusion of these team size fixed effects has little effect on the results.

A2 and A3 focus on team configuration. Table A2 repeats the analyses of Table 4, examining whether ordinary authors experience especially large citation losses in the presence of an eminent coauthor. Table A3 repeats the analysis of Table 5, examining whether the citations losses are milder in the presence of rookie coauthors.[30]

4.2.1 Recent Papers

Older papers may receive fewer ongoing citations, and no paper can receive less than zero citations after retraction. Because eminent authors are more senior and may have an older distribution of papers than ordinary authors do, this tendency could contribute to smaller citation losses among the relatively eminent. Figure A4 shows that the mean annual citations to treated papers falls to two in the tenth year since publication and falls to one in the fifteenth year since publication. We therefore reconsider our analysis excluding prior articles published more than ten years earlier than the retraction year. As a result, 69.8% of treated papers and 50.5% of paper-year observations are kept in the subsample.

Tables A1-A3 reconsider our core findings for this restricted sample, with the results presented in column (2) in each table. We see that the results are robust. For example, in Table 5, citations fall by 14.4% for lower-standing authors after retraction and the difference with eminent researchers is 11.0%, which is very similar to the results for the main sample. The results for team configuration in Tables A2 and A3 are again robust, with similar magnitudes and statistical significance as with the main specifications.

4.2.2 Actively Cited Papers

A related approach restricts the sample to publications that are being positively cited at the time of retraction. This issue is somewhat different from old papers per se because zero

[30] For focus and brevity, these analyses use the h-index as the measure of author standing. Appendix Tables A4-A13 provide additional results using the other standing measures.

citations could occur soon after publication, especially for ordinary authors who do not have many high quality publications. To deal with this issue, we exclude all prior work that has zero citations in the year before retraction. Compared to the main sample, this subsample includes 68.9% of treated papers and 59.1% of paper-year observations. The results are presented in column (3) of Tables A1-A3. We see again that the results all remain robust.

4.2.3 Citation Distance

Another related issue is that the (relatively abundant) prior work of eminent authors may on average be farther in idea space or social space from the retracted paper. To the extent that scientific communities and reputations tend to be field-specific, eminent authors may experience relatively mild citation declines on average if their prior work tends to sit outside the focal field and community of the retraction.[31] To assess this possibility, we reexamine our results in a sample restricted to low citation distance from the retracted paper. Namely, we consider the differential effects of author standing within the subsample of treated papers that are one degree of separation in the backwards citation network from the retracted article (i.e., prior papers that were directly cited by the retraction article). This restriction is substantial: it reduces the treatment sample to only 10.8% of the treated papers and 8.0% of the paper-years observations.

Looking at Table A1 column (4), we see that once again ordinary authors experience large citation losses to their prior work and that this effect is substantially offset for eminent authors. The magnitudes are somewhat greater on both dimensions than with the full sample. Thus, the attenuation of citation losses that is seen with eminence appears robustly within the narrow sample of the most closely related prior work. This finding indicates that the relatively mild citation losses experienced by eminent authors comes not because they have more prior

[31] That said, it is less clear how such differences in prior work would explain our main results around team configuration – i.e., that ordinary authors experience worse losses in the presence of eminent coauthors and milder losses in the presence of rookies.

work that is more distant, but rather appears among uniformly "near" prior work. Tables A2 and A3 tend to show broadly similar results to the main sample although with somewhat greater noise, which is perhaps not surprising given the large drop in sample size. The exacerbating role of eminent coauthors on ordinary coauthors is noisier than in the main sample (Table A2), while the attenuating role of rookie coauthors is similar and slightly larger than in the main sample (Table A3). Table A6 considers these results with a broader range of standing measures and shows similar and more statistically significant results using other standing measures.

Note also that, since we use self-citations to compile prior work for a given author, our sample is relatively likely to capture an author's prior work in closer fields (Wuchty et al, 2007) but may more weakly capture prior work written by that author in distant fields. If retraction effects weaken with distance from the focal field, and if eminent coauthors are more likely than less established teammates to have diverse research areas, then sampling closely-related work would tend to understate the magnitude of the Reverse Matthew Effect. That is, the differential advantage of eminence would be greater than the advantage already seen in the empirical results.

Overall, after restrictions on the treated sample, including by age of prior work, ongoing citations to prior work, or citation distance to prior work, we see that within "near" prior work, the findings continue to be characterized by relatively large citation losses for ordinary authors, relatively muted losses for eminent authors, and broadly similar amplification/attenuation of losses depending on the presence of eminent or rookie team members,

4.2.4 Citation Losses Excluding Self Citations

Retractions may also affect future publishing prospects, and differentially for eminent and non-eminent authors. The decline in citations to prior work might then potentially reflect less a direct community response to the prior work and more a decline in the capacity of the authors to cite their own prior work, once any differential retraction effects on an author's career take hold. To further focus on the community response, we reconsider the analysis excluding self-citations from the citation counts. These results are presented in column (5) of Tables A1-A3. The findings are very similar to the earlier results. Interestingly, the magnitudes of the citation effects are, if anything, slightly larger. This finding, which nets out self-citations, further points toward the negative spillover effect on prior work coming from the broader community, as opposed to the citation behavior of the retraction authors themselves.

4.2.5 Further Robustness Checks

We conduct a series of additional robustness checks estimating different samples and different models. First, we replace our Poisson estimation with OLS estimation. The OLS results are reported in column (6) of Tables A1-A3 and appear broadly similar to the Poisson results. Second, we explore the main results again clustering the standard errors by treatment-control paper group instead of retraction event. These results, presented in column (7) of Tables A1-A3, are seen to strengthen the statistical precision and confirm that the results we have presented are conservative. Third, we consider an alternative and noisier set of control papers, taking the 9th and 10th nearest controls for each treated paper, rather than the two nearest controls. As shown in column (8) of Tables A1-A3, the magnitudes of the results appear broadly similar although, not surprisingly, the noisier controls lead to somewhat less precise estimates. Fourth, we separate out prior work that has a short citation history before retraction, which could hurt our ability to find effective counterfactual controls. We address this issue by excluding all prior work published within three years before retraction. Results are shown in column (9) of Tables A1-A3 and appear similar to but slightly stronger than our baseline specification. Fifth, we consider a specification that also includes author position (first, middle and last) to control for the author's role in the retracted teamwork and, as shown in column (10) of Tables A1-A3, the results are again robust.[32] This last specification will be further discussed in Section 5.

4.2.6 Placebo Test

As a final check on our approach, we consider a placebo exercise to see whether the evolution of control paper citations is sensitive to author standing in the absence of retraction. In particular, using our control papers, we examine whether papers matched according to very similar initial citation patterns also have similar later citation patterns regardless of standing.[33] We find that standing does not predict future citation paths, conditional on initially similar citation paths, as detailed in Table A14. This analysis further suggests that our control strategy is effective for estimating counterfactual citation paths in the absence of retraction.

5. Interpretations and Discussion

The above empirical analyses establish several striking facts regarding retraction shocks and their differential effects across team members. We call these results a "Reverse Matthew Effect", as they echo the ideas that animate Merton's Matthew Effect, only now in the reverse case where we consider bad events. We find that retraction shocks lead to substantial declines in citations to the prior work of ordinary coauthors. By contrast, for eminent coauthors, retraction shocks provoke much less if any citation loss to their prior work. Furthermore, citation losses for ordinary coauthors are especially severe in the presence of an eminent coauthor on the retracted publication but less severe in the presence of rookie coauthors.

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[32] An alternative test includes the career age of an author in the regressions to control for the author's role in the retracted paper. Career age is measured by the difference between retraction year and the year when the author's first paper was published. See Table A13 in the online appendix.

[33] Specifically, we take a random sample of 500 pairs of control papers. For each author on these 1,000 papers, we then build their body of prior work and determine the eminence measures for each author. By construction, each control paper in a given pair has similar citation behavior up to the retraction event year. We then analyze whether control papers with higher standing authors diverge in their citations, after the retraction event year, from control papers with lower standing authors.

This section further discusses the empirical results in light of the ideas that Merton proposed. Returning to Merton's credit mechanism, we first formalize the idea that the community makes ex-post inferences about individual contributions in team settings given prior reputations and the uncertainty over who was responsible for the output. A simple Bayesian model of this mechanism is shown to provide a parsimonious, candidate explanation for the empirical results. We then discuss potential alternative interpretations and examine a falsification test where the community can easily infer the bad actor.

5.1 A Model

Let there be two types of agents, who differ in their tendency to produce "good" output. The community does not observe an individual's type directly but rather makes inferences about it by observing the individual's output. The community's belief about the individual's type characterizes that individual's reputation.[34] In particular, let an output have a quality characteristic that takes one of two states, $Y \in \{Y_{good}, Y_{bad}\}$. An individual can have a high or low tendency to produce good output. Let an individual's type be $\theta \in \{H, L\}$, representing a "high" and "low" type individual, respectively, where the low type produces "bad" output with a greater frequency than the high type

$$\Pr[Y_{bad}|L] > \Pr[Y_{bad}|H] \tag{4}$$

and we use the shorthand $p_\theta = \Pr[Y_{bad}|\theta]$. An individual's "reputation", R, is defined as the probability that the individual is the high type, $R = \Pr[H]$. In summary, the background probability of producing bad output depends on the author's type. How to distinguish the type given the observed output is the heart of the inference problem.

[34] In our empirical context, a "bad" output concerns the possibility that a given paper, regardless of how important it may otherwise seem, contains a severe enough mistake so that the paper will be retracted (i.e., the paper is not actually true). Reputation in thus based on the tendency of an author to have survived scrutiny of their prior work. Since scrutiny of an author is increasing in the amount of their prior work (and the attention paid to it), eminent authors without prior retractions can better establish reputations for not producing bad output.

5.1.1 Solo Production

To develop basic intuition, first consider the reputational updating for an individual who, working alone, produced output with characteristic Y. Let the individual i have a given prior reputation, R_i. Bayes rule says that the posterior belief about i's type, which we denote $R_i{'}$ is

$$R_i^{'} = \Pr[H_i|\mathrm{Y}] = \frac{\Pr[Y|H_i]\Pr[H_i]}{\Pr[Y]}.$$

Using the law of total probability in the denominator and definitions above, we can thus express the reputational change upon retraction as

$$\frac{R_i^{'}}{R_i} = \frac{1}{R_i + \frac{\Pr[Y|L]}{\Pr[Y|H]}(1 - R_i)}. \tag{5}$$

Given that low types are more likely to produce bad output, as defined in (4), it follows by inspection of (5) that the individual's reputation will fall after a bad event and rise after a good event.[35] Note also that in the extreme case, where $R_i = 1$, the individual is fully protected from the reputational consequences of retraction; as is standard with a Bayesian model, having a tight prior about the individual means that new events will have little further effect on beliefs.

5.1.2 Team Production

We now consider the richer case of team production, which allows us to characterize how the reputation of one team member can influence the credit another receives. In particular, let the output be produced by a team of two people, indexed $i \in \{1,2\}$, who have independent

[35] We have defined $\Pr[Y_{bad}|L] > \Pr[Y_{bad}|H]$. Therefore, for a bad event the denominator is greater than 1 and the reputation deteriorates. For a good event, it also follows from (4) that $\Pr[Y_{good}|L] < \Pr[Y_{good}|H]$ and so the denominator is less than 1 and reputation improves.

priors.[36] Again following Bayes' Rule, the two-person analogue to the reputational updating problem after an event with characteristic Y is now[37]

$$\frac{R_1^{'}}{R_1} = \frac{1}{R_1 + \frac{\Pr[Y|L_1, L_2](1-R_2)+\Pr[Y|L_1, H_2]R_2}{\Pr[Y|H_1, L_2](1-R_2)+\Pr[Y|H_1, H_2]R_2}(1 - R_1)}. \quad (6)$$

Reputational updating for the given team member thus depends on three elements: (a) the team member's own prior reputation, R_1; (b) the prior reputation of the other team member, R_2, raising the possibility of Matthew Effect type outcomes; and (c) the production technology mapping individual types to joint output. This last feature is encapsulated by the $\Pr[Y|\theta_1, \theta_2]$ terms.

5.1.3 The Reverse Matthew Effect

As seen in (6), the reputational update will depend on the production technology for the (observed) joint output characteristic, Y. That is, how do the individual contributions of the team participants determine the probability of a given output state? In the context of our empirical analysis, we focus on bad events, where the paper is false. For clarity, and to emphasize the "Reverse Matthew Effect" case, we can use $Y_{good} = 1$ representing that the output is "true" and $Y_{bad} = 0$ representing that the output is "false".

The production technology for false output may naturally have a "weak link" technology. That is, if an input to the paper is false (the data is faked, the empirical or computational analyses are wrong, etc.), the paper itself turns out to be false, so that the quality of the joint output is

$$Y = \min\{y_1, y_2\}$$

[36] The assumption of independent priors is made for simplicity. In team production, individuals may have produced together before and thus the priors may not be fully independent. While that case may be interesting, our goal here is to provide the simplest characterization for our empirical results.

[37] In particular, by Bayes' Rule, the posterior belief about the quality of individual 1 can be written

$$R_1' = \Pr[H_1|\mathrm{Y}] = \frac{\Pr[Y|H_1, L_2]\Pr[H_1, L_2] + \Pr[Y|H_1, H_2]\Pr[H_1, H_2]}{\Pr[Y]}$$

Using the law of total probability to rewrite $\Pr[Y]$, the definition of R_1 , and rearranging, one obtains the expression in the text.

where the individual contribution is $y_i \in \{1,0\}$, representing a true or false input, respectively. With this production technology, the probability that the joint output is false is then $\Pr[Y=0|\theta_1,\theta_2] = 1-(1-p_{\theta\,1})(1-p_{\theta\,2})$, where $p_\theta = \Pr[y=0|\theta]$. Reputational updating will occur according to the following Lemma.

Lemma (Reverse Matthew Effect)

(i) $R_1^{'} \leq R_1$; (ii) $\lim_{R_1 \to 1} R_1^{'}/R_1 = 1$; (iii) $\frac{\partial\left(R_1^{'}/R_1\right)}{\partial R_2} \leq 0$; and (iv) $\lim_{R_1 \to 1}\left(\frac{\partial\left(R_1^{'}/R_1\right)}{\partial R_2}\right) = 0$.

The proof is given in the appendix.

These results can capture the empirical findings and provide some precise intuition for them. The first result states that reputation declines upon retraction. This result corresponds to the broad finding where the team members experience citation losses on average to their existing work. It is also consistent with the retraction penalties reported in Lu et al. (2013) and Azoulay et al. (2017). The second result states that a high reputation acts to limit the reputational decline from the retraction. This result corresponds to the findings in Table 2, where an already eminent team member experiences more limited negative consequences on average.

The last two results focus on the reputational entanglement across individuals that may emerge in a teamwork setting and thus speak most precisely to a "Reverse Matthew Effect". The third result states that the greater the reputation of your teammate, the worse the effect on you. Thus, the Bayesian model predicts that the presence of an eminent team member exacerbates the reputational losses for the other team member. At the same time, the fourth result shows that eminence is protective against this spillover effect. Thus, while an eminent teammate can hurt you, it does not hurt you if you yourself are eminent. These theoretical results are closely consistent with the findings in Table 4, where ordinary authors experience worse effects the more eminent the coauthor (result iii), yet eminent authors see little effect from eminent coauthors (result iv). The empirical results in Table 5 also broadly correspond to these findings, where now we consider what happens when someone is paired with especially junior coauthors (i.e., rookies). Ordinary authors experience much smaller citation losses when paired with rookies (result iii), while eminent authors see relatively little influence from rookies (result iv).

These results are all intuitive in a Bayesian context, where the community is trying to infer the source of a mistake and must adjudicate between the team members and the background chance of a mistake. A well-established reputation deflects blame away from you and toward both your teammate and background bad luck. If the teammate also has a well-established reputation, then the community will tend to blame background bad luck, and both individuals face relatively mild consequences. An unformed reputation, however, attracts blame, and the more so the better your teammate's reputation. Overall, this theoretical approach can provide a natural and parsimonious interpretation of the key empirical results of the paper.[38]

It is useful to compare Azoulay et al. (2017)'s model with ours. Azoulay et al. (2017) assume that research communities can classify whether a retraction is due to misconduct or honest mistake. If the research community already agrees that a retraction event is due to misconduct of an identifiable bad actor, the retraction will tarnish the bad actor's reputation. If the community characterizes a retraction as honest mistake, it attributes the retraction to background noise hence does not update much on the author's reputation. This explains why Azoulay et al. only find significant retraction penalties in the cases of fraud or misconduct but not in the cases of honest mistakes. In comparison, we focus on the events where there is

[38] While we are unaware of any data analysis showing how credit from good events is allocated, one might also deploy Bayesian reasoning to inform the primitives for such a "classic" Matthew Effect. Entanglements across parties, and hence Matthew Effects, occur when the inputs of an individual agent cannot be directly inferred from the joint outcome. A classic Matthew Effect can then follow along Bayesian lines when either individual team member might provide the key contribution and determine the project's success. In particular, if either individual could drive great output from the team (e.g., by shaping the research question, major insight, or research approach the team uses) then the community must then again make inferences about individual credit, and this inference that will depend on the prior reputations of the individual team members.

significant uncertainty as to who contributes to the bad output in a team-produced single retraction. In light of the information uncertainty, our theory describes how the community makes inference from the bad outcome and each author's prior reputation.

5.2. An Alternative Credit Inference Hypothesis

Within the class of credit inference explanations, an alternative inference problem involves task allocation within the team. In particular, one may argue that science teams feature a hierarchal nature; eminent authors typically lead in the conceptual design of the research rather than in the technical analysis, where problems are more likely to emerge. In this view, eminent authors may receive less blame when retraction occurs because they are seen as unlikely to be responsible for the relevant tasks.

One way to test this idea is to control for position in the author list for the retracted paper. Noting that positioning in the author list typically informs the hierarchy of the team in science and engineering, we reconsider our main results adding dummies variables for the last author (usually the principle investigator) and middle authors (who play lesser roles). As shown in Column 10 of Tables A1-A3, adding such author-position variables to the regression model has little effect on the main results.[39]

Another way to test this idea is to examine citation effects based not on author eminence at the time of the retraction but at the time the research was conducted, when task allocation would be determined. To do so, we constructed past-standing measures using the eminence measures for an author in the year the problem paper was published. Then we examined both types of author standing (at the time of retraction and at the time of publication) in the regression. For ease of interpretation, both types of standing are measured by a dummy for

[39] Table A1 provides the regression results with these additional coefficients reported. The author position fixed effects in these regressions are found to be highly insignificant.

whether the absolute standing is in the top 10 percentile of all treated authors at that time. As shown in the first three columns of Table A15, being eminent at the time of retraction substantially reduces the citation losses using two of the three standing measures, while being eminent at the time of publication does not. This result appears inconsistent with a task allocation hypothesis. The last three columns of Table A15 restrict the sample to authors who had ordinary standing when the problem paper was published. Some of these authors became eminent and others remained ordinary by the time of retraction. The results suggest that ordinary authors who became eminent later, measured by total publications or h-index, see little if any citation loss. These results further suggest that task allocation does not appear to be a key explanation for our main findings.

5.3 "Bad Actors" as a Falsification Exercise

We can further conduct a falsification test by studying a context where the guilty actor is obvious and hence prior reputation should no longer matter in allocating blame across team members. Namely, we can study "multiple retraction" episodes where a single common author appears across multiple team-authored papers that were retracted. These cases point strongly at the common author as the blameworthy party. To undertake this analysis, we repeat our sampling and econometric strategy for all multiple retraction cases in the WOS where there is a single common author.[40] We define a "bad actor" as the common author across these multiple retraction case and define "innocent actors" as the coauthors on these retracted papers. Appendix Table A16 provides basic summary statistics for the multiple retractions cases.

Two additional features distinguish this exercise from the study of single retraction episodes. First, multiple retraction cases are more noteworthy events, often involving systematic

[40] That is, we collect the prior work of all authors involved in these retracted papers, match all their prior work to control papers, and calculated eminence measures for all of these authors. This is exactly the same procedure we followed for defining the treated sample, control sample, and eminence measures as in our primary sample of single retraction cases.

fraud, which can attract substantial, broad attention in the scientific community as well as in the public media. Hence the scale and scope of effects may naturally be different from single retraction events. Second, multiple retraction cases often occur over a string of years, which makes the timing in the econometric strategy less clean. To operationalize the analysis, we will use the retraction of the first paper to define the event year.

Table A17 presents the regression results. In column 1, we limit the sample to the "bad actors" and find that they experience large losses in citations to their prior work. This is consistent with Azoulay et al. (2017). In column 2, we limit the sample to "innocent actors" and find the interesting result that they experience citation increases to their prior work, which may reflect increased attention that comes to them and their work after retraction, as we discuss further below. In column 3, we consider the full sample of these authors. Here we see that the relative decline in citations for the "bad actors" appears especially large. Notably, and in line with the purpose of this falsification exercise, interactions with author standing are never statistically significant and are of inconsistent sign across specifications. Thus, prior reputation does not appear germane when the identity of the bad actor is known – either for the bad actors themselves or their innocent coauthors. This finding, as a falsification exercise, can further support an inference-based interpretation of our main results: prior reputation matters in episodes when the identity of the responsible actor is unclear.

5.4 The Communication Hypothesis

Merton's Matthew Effect also emphasizes a "communication" hypothesis, where eminence attracts attention to the output and for which there is evidence in the literature (Simcoe and Waguespack 2011, Azoulay et al. 2013). In the standard Matthew Effect, which considers "good" events, this communication effect may help the less established team member, offsetting the credit sharing issue. Namely, even if the less established team member receives little credit *share*, a widely noticed output can make the impact large in absolute terms. With a "bad" event, the communication hypothesis could exacerbate effects on less established team members, as the presence of an eminent team member may make bad events more widely noticed.[41]

Our empirical analysis, which examines differential effects within a team, studies the credit allocation aspect of the Matthew Effect rather than the communications hypothesis, where attention can influence everyone in the team. The one place where we may see a suggestive role of attention per se is the case of innocent actors in the multiple retraction analysis of the prior section. Here we see that the innocent team members actually experience a gain in citations to their prior work, which is consistent with increased attention to these individuals (coupled with the community's inference that they are unlikely to be at fault). This finding is consistent with Simcoe and Waugespack (2011), although in this case the increased attention is not driven by eminence but rather newsworthy events.[42]

More generally, while a communication mechanism may be operating in our primary context of single retractions, it does not appear capable of providing an alternative explanation for the results. Namely, were this mechanism all that was happening, then eminence should worsen the citation losses in general. Given that we find the opposite result – that ordinary authors experience substantially worse effects than eminent authors – the communication hypothesis does not appear to dominate. Nonetheless, the basic communication mechanism may still be operating in tandem with other forces. For example, if high standing is protective, then

[41] That said, it is also possible that less eminent scholars have more to gain (or less to lose) from fraud and thus, in equilibrium, may experience greater scrutiny of their papers and hence be more susceptible to retraction ex-ante (Lacetera and Zirulia 2011). Interestingly, this theoretical insight provides another way in which eminent scholars have an advantage with regard to retraction.
[42] The finding for innocent team members is also consistent with other potential mechanisms, such as the rallying of support around individuals who are seen as innocent victims.

the communication channel may worsen things more for the less eminent in the presence of eminent team members, exacerbating the credit inference effects.[43]

6. Conclusion

We have considered a natural experiment to assess consequences of bad events in team production. Our empirical context investigates journal article retractions in the sciences and demonstrates a striking asymmetry: Eminent authors experience little or no change in citations to their prior work after a coauthored retraction, while less eminent coauthors experience large citation losses, and especially in the presence of an eminent coauthor. We thus find a "Reverse Matthew Effect," developing Merton's canonical ideas about team production, showing that the less established team members appear especially vulnerable in the aftermath of negative events.

While our setting is scientific teamwork, the primitives of our setting – collaboration across individuals, difficulty in directly observing individual inputs, and differential reputations – generalize across many production contexts. For example, entrepreneurial teams mix publicly unobserved inputs into a collective output, and judgments about which individuals shaped the outcome may create important reputational consequences for serial entrepreneurs in attracting future financing and new teams.[44] Medical errors, legal malpractice, and accounting fraud may all suggest inference challenges in assigning individual blame for collective failures in surgery, litigation and accounting practices. Similarly, the financial performance of venture capital, private equity, and hedge funds may all bear on the reputations of the individuals in the investment team. The Reverse Matthew Effect would suggest that bad outcomes may create especially large reputational damage for less established team members, and especially when the

[43] It is also possible that, in our empirical setting, retractions are sufficiently well noticed that the marginal additional communication effect of eminence is small. In that sense, catastrophes may be settings where credit inference mechanisms dominate communication mechanisms; for "good" events, the balance of these forces may be different.

[44] See, e.g., Hsu (2008) for evidence on the advantage of successful prior entrepreneurs in attracting future funding.

team includes well-established individuals. Empirical investigations of these additional contexts provide exciting avenues for future work.

The findings around credit sharing also raise a rich set of additional theoretical issues. The link between reward allocation and effort incentives is the subject of an enormous literature on relational contracts whose predictions depend on information structures and the contracting environment (e.g., Holmstrom 1982, Aghion and Tirole 1994, Rayo 2007). Other authors have considered credit-sharing implications for team assembly (e.g., Bar-Isaac 2007, Bikard et al. 2015), leading to multifaceted but somewhat ambiguous results.[45] More generally, literatures on the sources of team effectiveness (e.g., Cohen and Bailey 1997) and the emergence of teams within social networks (e.g., Reagans et al. 2004) also bear on the link between credit considerations and team formation. Given the empirical findings in this paper, in which reward allocation is found to be asymmetric across team members, further empirical and theoretical research on how reputational considerations influence team function and team assembly choices appears to be an important avenue for future work.

[45] For example, Costa and Vasconcelos (2010) show that a high-reputation or low-reputation partner may be preferred depending on whether solo production is possible and whether the potential quality advantage with a high-reputation partner exceeds the disproportional credit attributed to that partner. Taking a different approach, Bar-Isaac (2007) finds that partnering with less-established authors can provide better effort incentives for the team.

Appendix: Proof of Lemma

Lemma (Reverse Matthew Effect) (i) $R_1^{'} \leq R_1$; (ii) $\lim_{R_1 \to 1} R_1^{'} / R_1 = 1$; (iii) $\frac{\partial \left(R_1^{'} / R_1\right)}{\partial R_2} \leq 0$; and (iv) $\lim_{R_1 \to 1} \left(\frac{\partial \left(R_1^{'} / R_1\right)}{\partial R_2} \right) = 0$.

Proof

Recall equation (6), which we write here as

$$R_1^{'} / R_1 = \left[R_1 + \frac{a(1 - R_2) + bR_2}{b(1 - R_2) + cR_2} (1 - R_1) \right]^{-1}$$

where $a = 1 - (1 - p_{\mathrm{L}})^2$, $b = 1 - (1 - p_{\mathrm{L}})(1 - p_{\mathrm{H}})$, and $c = 1 - (1 - p_{\mathrm{H}})^2$.

Result (i) follows by noting that $\frac{a(1-R_2)+bR_2}{b(1-R_2)+cR_2} \geq 1$. This ratio exceeds 1, by inspection, noting from (4) that $a \geq b$ and $b \geq c$.

Result (ii) follows by inspection taking the limit in (6).

Result (iii) follows if $\frac{\partial}{\partial R_2} \left(\frac{a(1-R_2)+bR_2}{b(1-R_2)+cR_2} \right) \geq 0$. It can be shown that $\frac{\partial}{\partial R_2} \left(\frac{a(1-R_2)+bR_2}{b(1-R_2)+cR_2} \right) = \frac{b^2 - ca}{(b+(c-b)R_2)^2}$, so that the sign of this derivative is the sign of $b^2 - ca$. Returning to the underlying definitions of a, b, and c (see above), one can write $b^2 - ca = (p_L - p_H)^2 \geq 0$, proving the result.

Result (iv) follows by inspection of the first derivative of (6).

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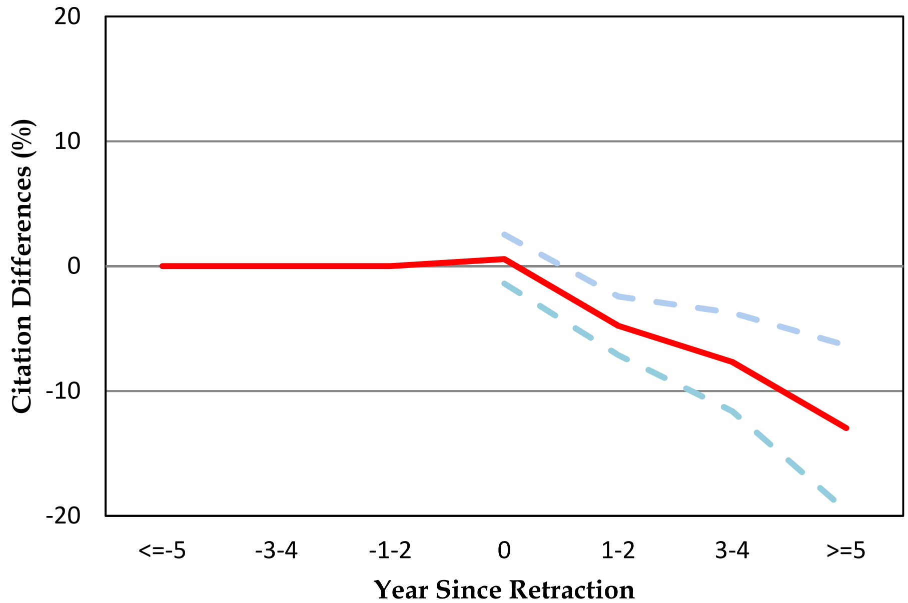
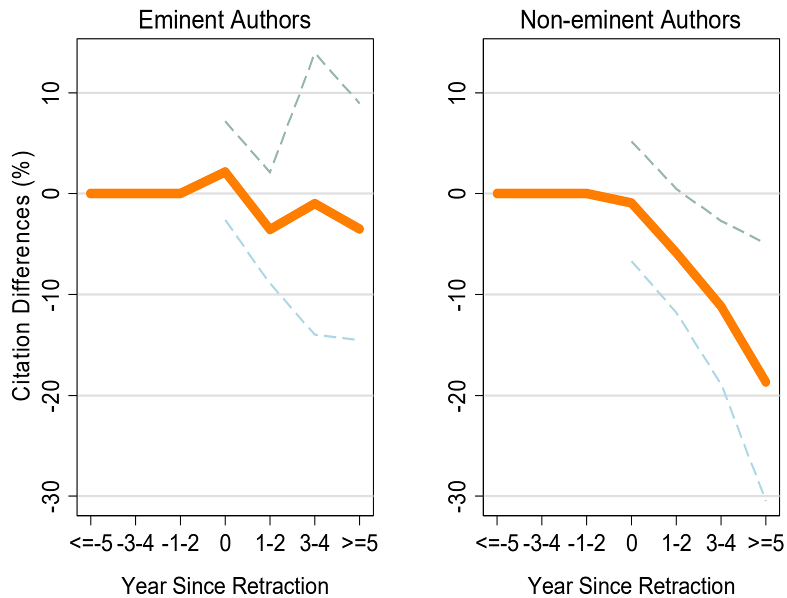
Figure 1: Citations to an Author's Prior Publications, Compared to Control Papers, by Years since Retraction Event



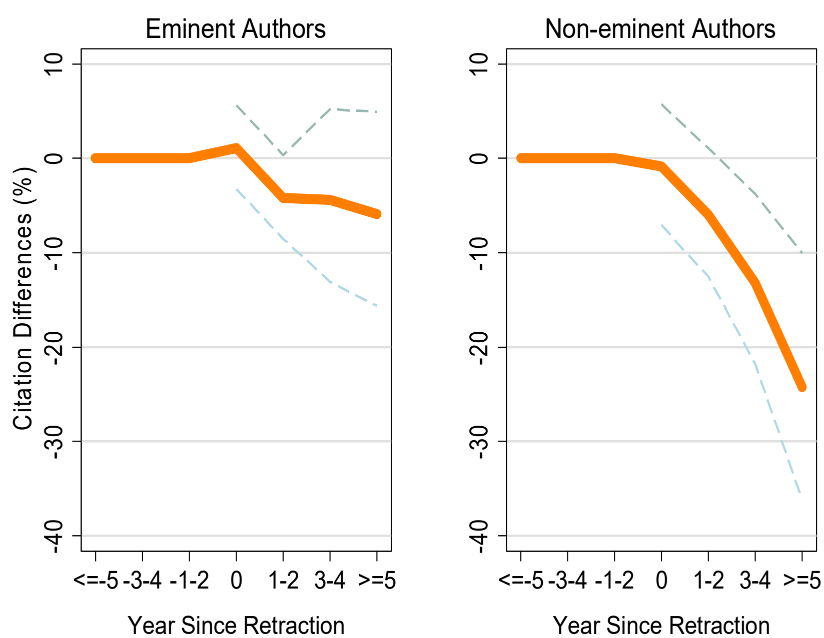
Note: This figure follows Lu et al. (2013) but restricts analysis to retraction events where the retracted paper was team-authored.

Figure 2: Citation Losses by Author Standing

Panel A: Absolute Standing



Panel B: Relative Standing



Notes: In Panel A, author are divided into two groups based on their absolute standing, where eminent authors are define as being in the upper 10th percentile by h-index (and non-eminent authors are everyone else). In Panel B, authors are divided according to relative standing within the team, where eminent authors are the individual with the highest h-index (and non-eminent authors are everyone else).

Table 1: Summary Statistics

Panel A: Unit of observation = author, treated only

Absolute Measures of Standing	Definition	Obs	Mean All	Mean Eminent	Mean Ordinary	SD	Min	Max
Prior Publications	total prior papers	732	24	136	13	46	1	452
Prior Citations	total prior citations	732	1071	8209	364	3570	0	67946
Prior h-index	prior h-index	732	10	44	6	14	0	132
Career Age	academic age till retraction	732	10	27	9	9	1	51

Notes: The eminent/ordinary authors are classified by prior h-index. We define an author as an eminent author if his or her prior h-index is among the top 10 percentile and 0 otherwise.

Panel B: Unit of observation = paper, treated only

	Retracted Papers	Prior Work
Paper Counts	276	10,209
% Published in 2000s	86.2%	45.5%
% Published in 1990s	13.8%	40.0%
% Published in 1980s	0%	14.5%
Yearly Mean Citation Count[(a)]	3.9	3.0
Mean Age Since Publication[(b)]	5.3	11.6
Mean Age at Retraction[(c)]	2.2	8.5
Mean Authors per Paper	5.9	5.4

Notes: (a) Mean citation rate is the rate in years prior to the retraction event (b) Age since publication is the difference between 2009 (the end of our sample) and the publication year; (c) Age at retraction is the difference between the year of the retraction event and the publication year. Note that control papers, by construction of the matching process, have exactly the same publication year, mean citation counts and dynamics prior to retraction, and age at retraction.

Table 2: Effect of Retraction on Citations to Prior Work, by Absolute Standing of the Author at Time of Retraction

Absolute Standing of the treated author	Standing Measures		
	Total # of prior papers	Total # of prior citations	H-index
	(1)	(2)	(3)
Treated*Post(t>=1)	-0.093**	-0.101***	-0.114***
	(0.039)	(0.034)	(0.040)
Author Standing*Treated*Post(t>=1)	0.040	0.030**	0.029**
	(0.036)	(0.012)	(0.015)
Author-Paper Fixed Effects	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y
Observations	419,239	419,239	419,239
Number of unique papers	34,562	34,562	34,562

Notes: Author standing refers to the noted empirical measure of eminence for a treated author in the year prior to retraction, standardized by sample mean and standard deviation. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table 3: Effect of Retraction on Citations to Prior Work, by Author Standing Relative to Coauthors at Time of Retraction

Standing of a treated author relative to the coauthors within the team	Top 1 in Total # of prior work	Top 1 in Total # of prior citations	Top 1 in h-index	Top 2 in Total # of prior work	Top 2 in Total # of prior citations	Top 2 in h-index
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post(t>=1)	-0.114**	-0.119***	-0.119***	-0.175***	-0.151***	-0.154***
	(0.044)	(0.045)	(0.045)	(0.046)	(0.055)	(0.052)
Author Standing*Treated*Post(t>=1)	0.065	0.074*	0.072*	0.121***	0.095*	0.097*
	(0.042)	(0.043)	(0.043)	(0.046)	(0.056)	(0.053)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y
Observations	419,239	419,239	419,239	419,239	419,239	419,239
Number of unique papers	34,562	34,562	34,562	34,562	34,562	34,562

Notes: See notes for Table 2. The difference here is that author standing is now a dummy for whether a treated author had the highest standing (“Top 1”) within the team or is among the two individuals with highest standing (“Top 2”) in the team.

Table 4: Effect of Retraction on Citations to Prior Work, by Own and Coauthor Standing

Team configurations in the retracted paper	All Authors		
	Total # of prior work	Total # of prior citations	Prior h-index
	(1)	(2)	(3)
Treated*Post(t>=1)	-0.016	-0.059	0.009
	(0.037)	(0.076)	(0.029)
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)	-0.029	-0.002	-0.056
	(0.061)	(0.093)	(0.060)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)	-0.123*	-0.126	-0.165**
	(0.067)	(0.097)	(0.082)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)	-0.063	0.009	-0.101*
	(0.064)	(0.089)	(0.057)
Author-Paper Fixed Effects	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y
Observations	419,239	419,239	419,239
Number of papers	34,562	34,562	34,562

Notes: We classified the authors into four groups using dummy variables indicating whether (1) own standing is ordinary and the highest-standing coauthor is ordinary, (2) own standing is ordinary but a coauthor is eminent, (3) own standing is eminent and the highest-standing coauthor is ordinary, and (4) own standing and a coauthor are both eminent (the omitted category in the regression). Author standing is measured in the year prior to retraction. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table 5: Effect of Retraction on Citations to Prior Work, Accounting for Rookie Coauthors

	h-index		
Team configurations in the retracted paper	Full Sample (2)	Eminent (3)	Ordinary (4)
Treated*Post(t>=1)	-0.121***	-0.043	-0.119***
	(0.038)	(0.034)	(0.040)
Author Standing*Treated*Post(t>=1)	0.026**		
	(0.013)		
% Rookie*Treated*Post(t>=1)	0.073***	0.045	0.105***
	(0.025)	(0.031)	(0.033)
Author-Paper Fixed Effects	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y
Team Size*Treated*Post	Y	Y	Y
Observations	419,239	216,735	202,504
Number of unique papers	34,562	15,133	19,429

Notes: Author standing is measured in the year prior to retraction, and normalized by sample mean and standard deviation. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Appendix: Prior Work

We built the sample of prior work using the Web of Science database. Because different authors may share the same name, relying on the name alone to identify an author's body of work would result in an inaccurate sample. We therefore applied the following procedures, harnessing the citation network, to identify the authors' prior work.

- We compiled a list of retracted articles and obtained the names of authors for each article.
- We then exploited the citation network in the Web of Science to identify the articles cited by these authors that share the citing author's name. That is, we use the tendency of authors to self-cite to provide an algorithm for locating the author's broader body of work (Wuchty et al. 2007, Lu et al. 2013).
    - Specifically, we start by tracing citations from each retracted article to all referenced articles by the same author, and then use the citations from these prior articles to other prior articles by the same author and so on up to a point when additional prior work is no longer available.
    - Next, we use the obtained prior work to trace forward this citation network and locate papers by the same author that cite these past publications.
    - We use the retraction year as a cutoff to identify the authors' work published before the retraction.
    - Note that we exclude any prior work that was retracted itself.
    - Some prior publications will be counted more than once if multiple authors in the sample collaborated on them.

Prior publications identified in this way are highly likely to be written by the same author and they should capture most of the prior works that this author has written on a topic related to the retracted work (Wuchty et al. 2007, Lu et al. 2013). This algorithm may fail to capture the papers that are written by the same person but in completely unrelated areas. Possibly, it will include authors that are distinct people but share the same name and work in the same, specific research stream, as defined by the citation network, although simple estimations suggest that such mismatches are extremely unlikely, with Wuchty et al. (2007) estimating false matches in only 1 in 2000 cases. See Wuchty et al. (2007) and Lu et al. (2013) for further discussion.

Figure A1: Matching quality of control papers

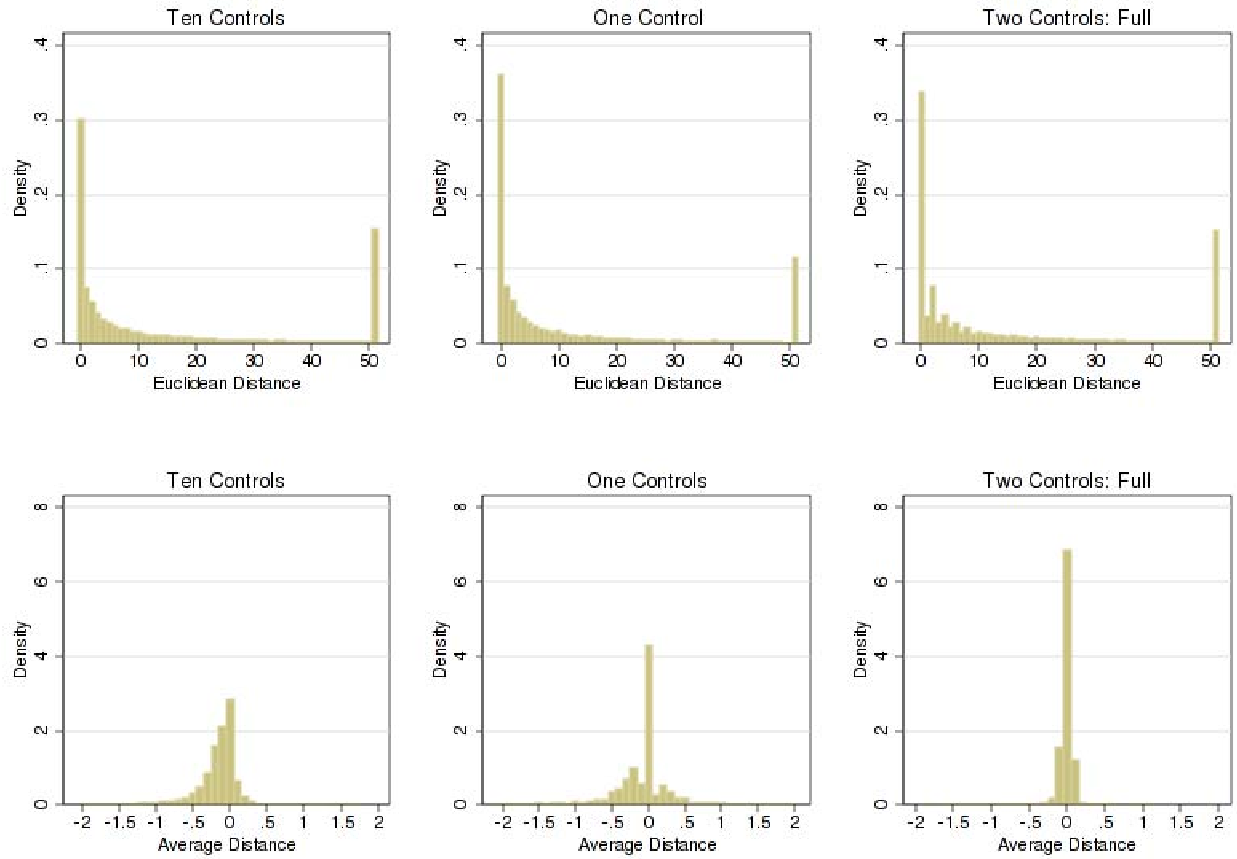
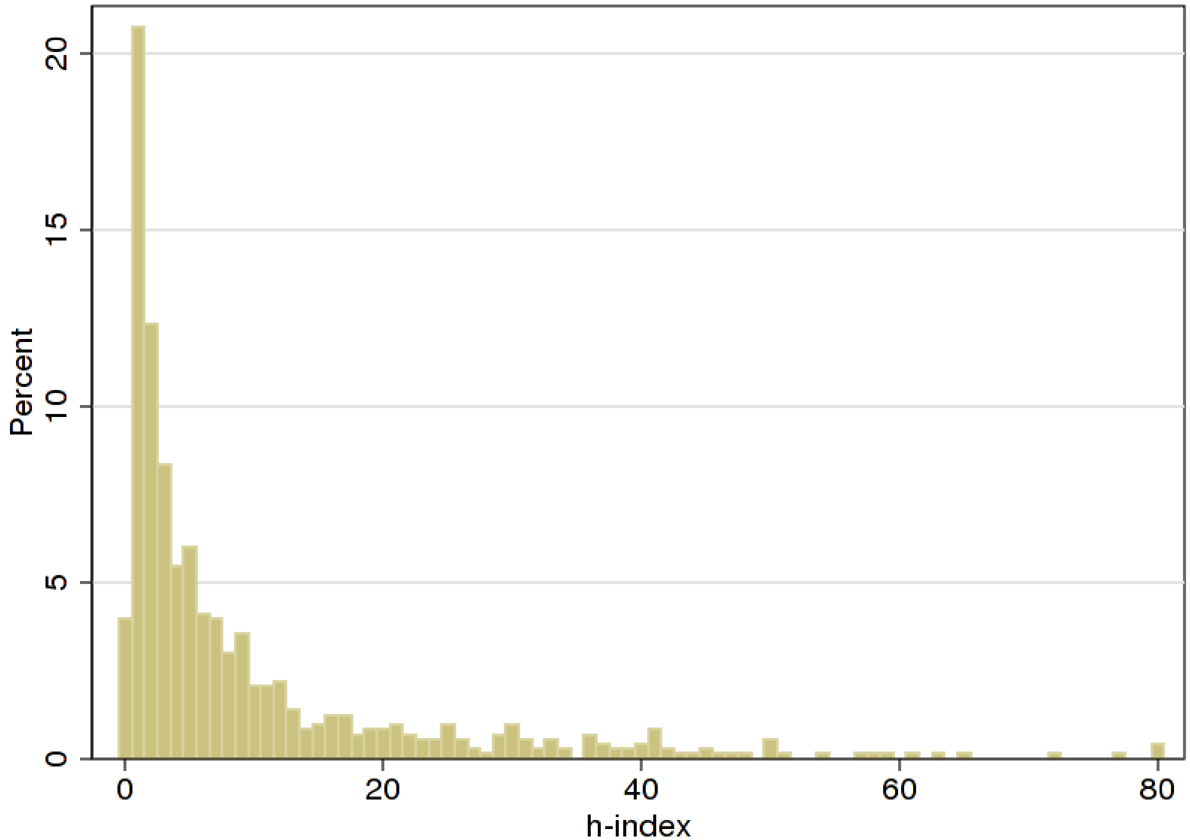
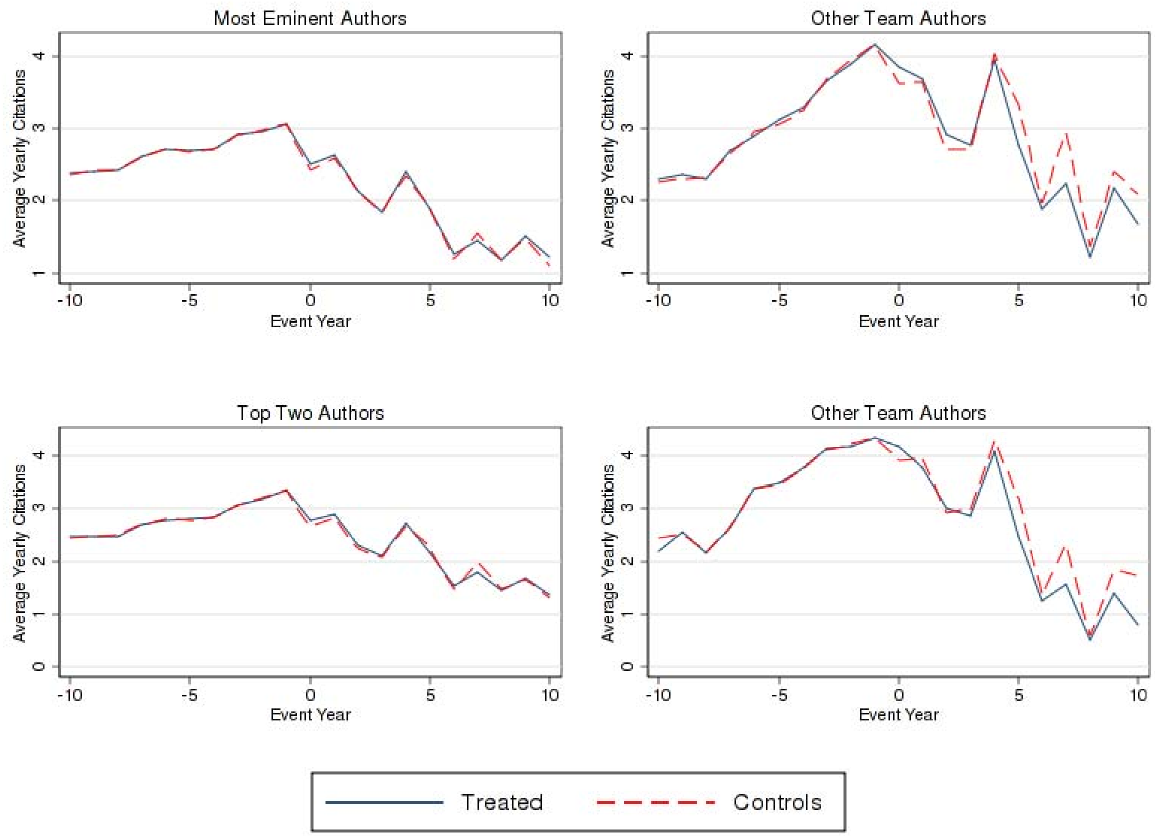


Figure A2: Distribution of h-index per treated author at the time of retraction



Note: we pool authors with an h-index greater than 80 at 80 in this figure.

Figure A3: Citations Before and After Retraction, by Author Standing



Notes: The solid blue line indicates the treated papers (prior publications of authors involved in the retraction), and the dashed red line indicates control papers. In the top row, "Other Team Authors" are all but the most eminent author in the team of the retracted paper. In the bottom row, "Other Team Authors" are all but the two most eminent authors in the team of the retracted paper.

Figure A4: citation life cycle of control papers

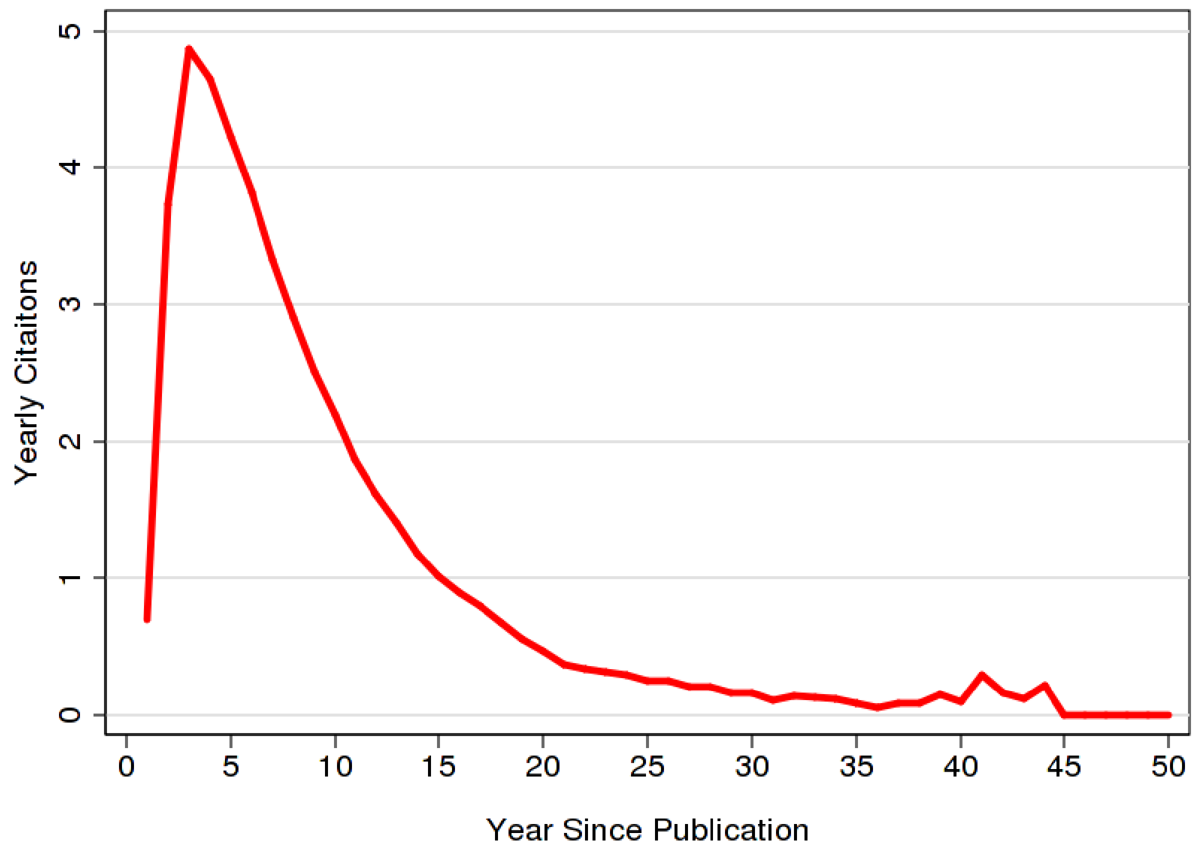


Table A1: Relative Standing of Coauthors, Additional Results

	Top 2 in h-index									
Status of a treated author relative to the other coauthors within the team	Baseline	Excluding old papers	Excluding papers not being cited	Low citation distance	Excluding Self-citations	OLS	Cluster by Treated Paper	More distant controls	Excluding short matching periods	Adding Author Positions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated*Post(t>=1)	-0.154***	-0.155***	-0.155***	-0.162**	-0.186***	-0.116**	-0.154***	-0.138**	-0.206***	-0.196**
	(0.052)	(0.051)	(0.055)	(0.066)	(0.055)	(0.046)	(0.041)	(0.063)	(0.068)	(0.081)
Realtive Eminence*Treated*Post(t>=1)	0.097*	0.104**	0.099*	0.163**	0.102*	0.084*	0.097**	0.081	0.128*	0.108*
	(0.053)	(0.050)	(0.056)	(0.080)	(0.055)	(0.043)	(0.040)	(0.065)	(0.070)	(0.055)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	419,239	211,788	247,686	33,691	418,128	419,239	419,239	419,019	359,273	419,239
Number of unique papers	34,562	24,121	23,814	3,738	34,361	34,562	34,562	34,523	25,187	34,562

Notes: This table repeats main results for relative standing but with various alternative samples and econometric specifications, as indicated by the heading to each column and as further explained in the text. The specification of Table 3 column (6) is repeated here in column (1) and provides the baseline specification against which the other analyses can be compared.

Table A2: Team Configuration, Additional Results

Status configurations of own and co-authors in the retracted teamwork	h-index									
	Baseline	Excluding old papers	Excluding papers not being cited	Low citation distance	Excluding Self-citations	OLS	Cluster by Treated Paper	More distant controls	Excluding short matching periods	Adding Author Positions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated*Post(t>=1)	0.009	0.016	0.011	-0.011	-0.031	0.004	0.009	0.008	-0.025	-0.017
	(0.029)	(0.032)	(0.028)	(0.013)	(0.046)	(0.034)	(0.032)	(0.024)	(0.044)	(0.075)
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)	-0.056	-0.056	-0.053	0.171	-0.027	-0.040	-0.056	-0.063	-0.038	-0.049
	(0.060)	(0.059)	(0.058)	(0.132)	(0.072)	(0.048)	(0.042)	(0.055)	(0.071)	(0.063)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)	-0.165**	-0.164**	-0.174**	-0.140	-0.174*	-0.129*	-0.165***	-0.161**	-0.210**	-0.159*
	(0.082)	(0.083)	(0.079)	(0.109)	(0.090)	(0.074)	(0.051)	(0.077)	(0.098)	(0.083)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)	-0.101*	-0.107*	-0.105*	-0.048	-0.092	-0.045	-0.101**	-0.089*	-0.082	-0.091
	(0.057)	(0.062)	(0.058)	(0.091)	(0.068)	(0.043)	(0.046)	(0.054)	(0.072)	(0.057)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Author-Paper Fixed Effects	419,239	211,788	247,686	33,691	418,128	419,239	419,239	419,019	359,273	419,239
Number of unique papers	34,562	24,121	23,814	3,738	34,361	34,562	34,562	34,523	25,187	34,562

Notes: This table repeats main results for team configuration in Table 4A but with various alternative samples and econometric specifications, as indicated by the heading to each column and as further explained in the text. The specification of Table 4A column (3) is repeated here in column (1) and provides the baseline specification against which the other analyses can be compared.

Table A3: Team Configuration Accounting for Rookie Coauthors, Additional Results

Standing configuration with the presence of rookie coauthors	h-index									
	Baseline	Excluding old papers	Excluding papers not being cited	Low citation distance	Excluding Self-citations	OLS	Clustered by Treated Paper	More distance controls	Excluding short matching periods	Adding Author Positions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated*Post(t>=1)	-0.121***	-0.115***	-0.124***	-0.062	-0.160***	-0.118*	-0.121***	-0.109***	-0.164***	-0.118*
	(0.038)	(0.040)	(0.038)	(0.070)	(0.041)	(0.067)	(0.028)	(0.037)	(0.044)	(0.067)
Author Standing*Treated*Post(t>=1)	0.026**	0.026*	0.030**	0.085**	0.031**	0.027*	0.026**	0.021	0.038**	0.027*
	(0.013)	(0.013)	(0.013)	(0.038)	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.014)
% No Prior*Treated*Post(t>=1)	0.073***	0.082***	0.073***	0.103*	0.087***	0.073***	0.073***	0.070***	0.083***	0.073***
	(0.025)	(0.026)	(0.025)	(0.059)	(0.027)	(0.025)	(0.018)	(0.026)	(0.025)	(0.025)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Team Size*Treated*Post	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	419,239	211,788	247,686	33,691	418,128	419,239	419,239	419,019	359,273	419,239
Number of unique papers	34,562	24,121	23,814	3,738	34,361	34,562	34,562	34,523	25,187	34,562

Notes: This table repeats the main results for team configuration in Table 4B but with various alternative samples and econometric specifications, as indicated by the heading to each column and as further explained in the text. The specification of Table 4B column (1) is repeated here in column (1) and provides the baseline specification against which the other analyses can be compared.

Table A4: Effect of retraction on citations to prior work, excluding old papers

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.090**	-0.096***	-0.109***	-0.178***	-0.153***	-0.155***	0.008	-0.052	0.016
	(0.041)	(0.036)	(0.042)	(0.046)	(0.053)	(0.051)	(0.033)	(0.090)	(0.032)
Author Standing*Treated*Post(t>=1)	0.042	0.030**	0.029**	0.131***	0.102*	0.104**			
	(0.037)	(0.012)	(0.014)	(0.045)	(0.053)	(0.050)			
Self is eminent and Co-author is ordinary							-0.047	-0.009	-0.056
***Treated*Post(t>=1)**							(0.057)	(0.102)	(0.059)
Self is ordinary and Co-author is eminent							-0.143**	-0.129	-0.164**
***Treated*Post(t>=1)**							(0.066)	(0.104)	(0.083)
Self is ordinary and Co-author is ordinary							-0.089	0.007	-0.107*
***Treated*Post(t>=1)**							(0.065)	(0.102)	(0.062)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	211,788	211,788	211,788	211,788	211,788	211,788	211,788	211,788	211,788
Number of unique papers	24,121	24,121	24,121	24,121	24,121	24,121	24,121	24,121	24,121

For interpreting regression coefficients in columns (1)-(3) see notes for Table 2, for columns (4)-(6) see Table 3 and for columns (7)-(9) see Table 4A. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A5: Effect of retraction on citation of prior work, excluding treated papers not being cited

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.096**	-0.102***	-0.118***	-0.175***	-0.159***	-0.155***	-0.009	-0.061	0.011
	(0.039)	(0.034)	(0.040)	(0.044)	(0.056)	(0.055)	(0.031)	(0.078)	(0.028)
Author Standing*Treated*Post(t>=1)	0.045	0.030**	0.031**	0.121***	0.104*	0.099*			
	(0.037)	(0.013)	(0.015)	(0.045)	(0.058)	(0.056)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							-0.035	0.006	-0.053
							(0.057)	(0.093)	(0.058)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.142**	-0.129	-0.174**
							(0.062)	(0.096)	(0.079)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.070	0.010	-0.105*
							(0.062)	(0.090)	(0.058)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	247,686	247,686	247,686	247,686	247,686	247,686	247,686	247,686	247,686
Number of unique papers	23,814	23,814	23,814	23,814	23,814	23,814	23,814	23,814	23,814

Sample excludes treated papers that had zero citations in year before retraction. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A6: Effect of retraction on citation of prior work, treated papers at one degree of separation in the backward citation network

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.108	-0.108	-0.126	-0.168***	-0.156**	-0.162**	0.084***	0.028	-0.011
	(0.080)	(0.078)	(0.091)	(0.060)	(0.067)	(0.066)	(0.031)	(0.044)	(0.013)
Author Standing*Treated*Post(t>=1)	1.418*	0.255**	0.448*	0.176**	0.158*	0.163**			
	(0.814)	(0.126)	(0.261)	(0.078)	(0.082)	(0.080)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							0.047	0.061	0.171
							(0.122)	(0.128)	(0.132)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.256***	-0.189*	-0.140
							(0.092)	(0.102)	(0.109)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.137	(0.078)	-0.048
							(0.103)	(0.113)	(0.091)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	33,691	33,691	33,691	33,691	33,691	33,691	33,691	33,691	33,691
Number of unique papers	3,738	3,738	3,738	3,738	3,738	3,738	3,738	3,738	3,738

Sample includes only those treated papers that were directly cited by the retracted paper. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A7: Effect of retraction on citations to prior work, excluding self-citations

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.119***	-0.137***	-0.151***	-0.205***	-0.186***	-0.186***	-0.059	-0.087	-0.031
	(0.040)	(0.037)	(0.043)	(0.049)	(0.058)	(0.055)	(0.060)	(0.078)	(0.046)
Author Standing*Treated*Post(t>=1)	0.037	0.037***	0.035**	0.124**	0.103*	0.102*			
	(0.039)	(0.013)	(0.016)	(0.049)	(0.058)	(0.055)			
Self is eminent and Co-author is ordinary							-0.016	0.016	-0.027
***Treated*Post(t>=1)**							(0.080)	(0.096)	(0.072)
Self is ordinary and Co-author is eminent							-0.135*	-0.147	-0.174*
***Treated*Post(t>=1)**							(0.079)	(0.098)	(0.090)
Self is ordinary and Co-author is ordinary							-0.030	0.001	-0.092
***Treated*Post(t>=1)**							(0.081)	(0.092)	(0.068)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	418,128	418,128	418,128	418,128	418,128	418,128	418,128	418,128	418,128
Number of unique papers	34,361	34,361	34,361	34,361	34,361	34,361	34,361	34,361	34,361

For interpreting regression coefficients in columns (1)-(3) see notes for Table 2, for columns (4)-(6) see Table 3 and for columns (7)-(9) see Table 4A. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A8: Effect of retraction on log of citations to prior work, OLS

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top 2 in Total # of prior citations	Top 2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.056**	-0.064***	-0.070**	-0.129***	-0.118**	-0.116**	-0.034	-0.020	0.004
	(0.025)	(0.023)	(0.027)	(0.045)	(0.046)	(0.046)	(0.039)	(0.034)	(0.034)
Author Standing*Treated*Post(t>=1)	0.022	0.023**	0.019	0.098**	0.086*	0.084*			
	(0.023)	(0.011)	(0.012)	(0.042)	(0.044)	(0.043)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							0.007	-0.022	-0.040
							(0.049)	(0.048)	(0.048)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.087	-0.124*	-0.129*
							(0.061)	(0.066)	(0.074)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							0.005	(0.005)	-0.045
							(0.047)	(0.044)	(0.043)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	242,640	242,640	242,640	242,640	242,640	242,640	242,640	242,640	242,640
R-squared	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268	0.268
Number of unique papers	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562

All regressions are now ordinary least squares, with errors clustered by each retraction event. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A9: Effect of retraction on citation to prior work, clustering by treated paper–control group

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.093***	-0.101***	-0.114***	-0.175***	-0.151***	-0.154***	-0.016	-0.059	0.009
	(0.026)	(0.023)	(0.028)	(0.041)	(0.041)	(0.041)	(0.034)	(0.041)	(0.032)
Author Standing*Treated*Post(t>=1)	0.040*	0.030***	0.029***	0.121***	0.095**	0.097**			
	(0.021)	(0.009)	(0.010)	(0.041)	(0.040)	(0.040)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							-0.029	-0.002	-0.056
							(0.042)	(0.049)	(0.042)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.123***	-0.126**	-0.165***
							(0.045)	(0.055)	(0.051)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.063	0.009	-0.101**
							(0.050)	(0.054)	(0.046)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	419,239	419,239	419,239	419,239	419,239	419,239	419,239	419,239	419,239
Number of unique papers	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562

All regressions report coefficients from maximum likelihood estimation of a Poisson count model, but with errors now clustered by each treated paper control group. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A10: Effect of retraction on citation of prior work, using more distant controls

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.087**	-0.093***	-0.102***	-0.169***	-0.134**	-0.138**	-0.016	-0.063	0.008
	(0.037)	(0.033)	(0.039)	(0.053)	(0.065)	(0.063)	(0.046)	(0.065)	(0.024)
Author Standing*Treated*Post(t>=1)	0.033	0.024*	0.022	0.117**	0.077	0.081			
	(0.036)	(0.013)	(0.015)	(0.055)	(0.066)	(0.065)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							-0.032	0.006	-0.063
							(0.065)	(0.082)	(0.055)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.120*	-0.115	-0.161**
							(0.070)	(0.091)	(0.077)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.057	0.017	-0.089*
							(0.069)	(0.081)	(0.054)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	419,019	419,019	419,019	419,019	419,019	419,019	419,019	419,019	419,019
Number of unique papers	34,523	34,523	34,523	34,523	34,523	34,523	34,523	34,523	34,523

Controls papers are no longer the best two matches for each treated paper but the worst two matches within the set of 10 closest papers (i.e., the 9th and 10th closest matches). All regressions report coefficients from maximum likelihood estimation of a Poisson count model, with errors clustered by retraction event (statistical significance is greater when alternatively clustering by each treated paper control group). Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A11: Effect of retraction on citation of prior work, excluding treated papers published within three years before retraction

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work (1)	Total # of prior citations (2)	h-index (3)	Top 2 in Total # of prior work (4)	Top 2 in Total # of prior citations (5)	Top 2 in h-index (6)	Total # of prior work (7)	Total # of prior citations (8)	h-index (9)
Treated*Post(t>=1)	-0.125***	-0.134***	-0.152***	-0.247***	-0.218***	-0.206***	-0.060	-0.077	-0.025
	(0.044)	(0.039)	(0.048)	(0.057)	(0.068)	(0.068)	(0.055)	(0.073)	(0.044)
Author Standing*Treated*Post(t>=1)	0.052	0.036**	0.036**	0.174***	0.142**	0.128*			
	(0.042)	(0.015)	(0.018)	(0.059)	(0.071)	(0.070)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							0.005	-0.002	-0.038
							(0.076)	(0.093)	(0.071)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.143	-0.182*	-0.210**
							(0.088)	(0.105)	(0.098)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.039	0.010	-0.082
							(0.082)	(0.094)	(0.072)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	359,273	359,273	359,273	359,273	359,273	359,273	359,273	359,273	359,273
Number of unique papers	25,187	25,187	25,187	25,187	25,187	25,187	25,187	25,187	25,187

All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A12: Effect of retraction on citations to prior work, including author position on retracted paper

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work (1)	Total # of prior citations (2)	h-index (3)	Top 2 in Total # of prior work (4)	Top 2 in Total # of prior citations (5)	Top 2 in h-index (6)	Total # of prior work (7)	Total # of prior citations (8)	h-index (9)
Treated*Post(t>=1)	-0.128*	-0.127**	-0.136**	-0.213***	-0.191**	-0.196**	-0.055	-0.095	-0.017
	(0.066)	(0.063)	(0.063)	(0.079)	(0.082)	(0.081)	(0.081)	(0.104)	(0.075)
Author Standing*Treated*Post(t>=1)	0.037	0.029**	0.028*	0.128***	0.103*	0.108*			
	(0.037)	(0.013)	(0.015)	(0.046)	(0.057)	(0.055)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							-0.024	0.001	-0.049
							(0.062)	(0.091)	(0.063)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.124*	-0.124	-0.159*
							(0.070)	(0.096)	(0.083)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.055	0.016	-0.091
							(0.064)	(0.088)	(0.057)
Middle Author*Treated*Post(t>=1)	0.015	0.003	0.0001	0.002	0.002	0.001	0.007	0.006	0.001
	(0.080)	(0.076)	(0.078)	(0.077)	(0.074)	(0.077)	(0.077)	(0.078)	(0.078)
Last Author*Treated*Post(t>=1)	0.051	0.042	0.037	0.052	0.052	0.053	0.053	0.050	0.032
	(0.074)	(0.070)	(0.070)	(0.074)	(0.070)	(0.073)	(0.072)	(0.074)	(0.071)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	419,239	419,239	419,239	419,239	419,239	419,239	419,239	419,239	419,239
Number of unique papers	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562

For interpreting regression coefficients in columns (1)-(3) see notes for Table 2, for columns (4)-(6) see Table 3 and for columns (7)-(9) see Table 4A. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A13: Effect of retraction on citations to prior work, including author career age at the time of retraction

	Absolute Standing			Relative Standing			Team Configuration		
Measure of Author Standing	Total # of prior work	Total # of prior citations	h-index	Top 2 in Total # of prior work	Top2 in Total # of prior citations	Top2 in h-index	Total # of prior work	Total # of prior citations	h-index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated*Post(t>=1)	-0.117*	-0.113*	-0.110*	-0.188***	-0.168***	-0.170***	-0.053	-0.124	-0.003
	(0.063)	(0.064)	(0.064)	(0.055)	(0.061)	(0.059)	(0.090)	(0.134)	(0.075)
Author Standing*Treated*Post(t>=1)	0.022	0.026*	0.030	0.107*	0.078	0.079			
	(0.045)	(0.015)	(0.021)	(0.060)	(0.068)	(0.066)			
Self is eminent and Co-author is ordinary *Treated*Post(t>=1)							-0.029	-0.012	-0.057
							(0.062)	(0.080)	(0.060)
Self is ordinary and Co-author is eminent *Treated*Post(t>=1)							-0.102	-0.096	-0.158*
							(0.086)	(0.119)	(0.096)
Self is ordinary and Co-author is ordinary *Treated*Post(t>=1)							-0.042	0.035	-0.094*
							(0.067)	(0.102)	(0.056)
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	419,239	419,239	419,239	419,239	419,239	419,239	419,239	419,239	419,239
Number of unique papers	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562	34,562

For interpreting regression coefficients in columns (1)-(3) see notes for Table 2, for columns (4)-(6) see Table 3 and for columns (7)-(9) see Table 4A. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A14: Placebo Test

	Team Average (authors with prior)	Team Average (all authors)
Post(t>=1)	0.873***	0.867***
	(0.188)	(0.185)
Team Standing*Post(t>=1)	-0.014	-0.017
	(0.013)	(0.017)

Notes: We conduct a placebo test by randomly sampling 500 pairs of clean (i.e., non-retracted) papers from our control sample. By construction, each pair has similar citation patterns prior to the (pseudo) retraction date. We next determine the author eminence measures for each control paper and further calculate the average author eminence measures among each paper's authors. We then examine whether higher standing teams have different citation paths after the (pseudo) retraction event year for that pair. As can be seen from the interaction term in the table, the eminence measure has no predictive power for future citations. In other words, when two clean papers share similar citation patterns in the early stage, author eminence does not affect their citations in the later stage. Hence our control matches appear adequate to capture counterfactual citation paths, regardless of team standing.

Table A15: Effect of Retraction on Citations to Prior Work, Including Author Standing at Time of Publishing Retracted Paper

	Full Sample			Ordinary Authors at Publishing		
Author Standing Measures	=1 if total # of prior work is in top 10%	=1 if total # of prior citations is in top 10%	=1 if h-index is in top 10%	=1 if total # of prior work is in top 10%	=1 if total # of prior citations is in top 10%	=1 if h-index is in top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post(t>=1)	-0.098**	-0.086**	-0.105**	-0.097**	-0.082**	-0.105**
	(0.041)	(0.040)	(0.042)	(0.041)	(0.040)	(0.043)
Author Standing at time of retraction *Treated*Post(t>=1)	0.180**	-0.030	0.091*	0.194**	-0.054	0.106**
	(0.080)	(0.084)	(0.047)	(0.082)	(0.104)	(0.052)
Author Standing at time of publication *Treated*Post(t>=1)	-0.125	0.065	-0.018			
	(0.079)	(0.065)	(0.043)			
Author-Paper Fixed Effects	Y	Y	Y	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y	Y	Y	Y
Observations	419,239	419,239	419,239	182,967	204,801	198,182
Number of papers	34,562	34,562	34,562	17,702	19,251	18,922

Notes: An author is defined as ordinary at time of publication if her absolute standing measure was below the top 10 percentile of all treated authors at the time of publishing the (eventually) retracted paper. Author standing at time of retraction is defined similarly but in the year of retraction instead of the year of publication. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. All regressions include all one-way and two-way interactions terms; we do not report those coefficients for brevity. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A16: Summary Statistics for Multiple Retraction Cases as Used in the Falsification Exercise

Panel A: Unit of observation = author, treated only

Absolute Measures of Standing	Definition	Obs	MEAN	SD	Min	Max
Prior Publications	total prior papers	61	65	174	1	1278
Prior Citations	total prior citations	61	3717	14880	0	113069
Prior h-index	prior h-index	61	17	26	0	170

Panel B: Unit of observation = paper, treated only

	Single Retraction	Multiple Retraction
Paper Counts	10,209	1,175
% Published in 2000s	45.5%	32.9%
% Published in 1990s	40.0%	39.4%
% Published in 1980s	14.5%	27.7%
Yearly Mean Citations Count[(a)]	3.0	3.7
Mean Age Since Publication[(b)]	11.6	14.5
Mean Age at Retraction[(c)]	8.5	8.4

Notes: (a) Mean citation rate is the rate in years prior to the retraction event (b) Age since publication is the difference between 2009 (the end of our sample) and the publication year; (c) Age at retraction is the difference between the year of the retraction event and the publication year. Note that control papers, by construction of the matching process, have exactly the same publication year, mean citation counts and dynamics prior to retraction, and age at retraction.

Table A17: Falsification Exercise using Multiple Retraction Cases

Absolute Standing of the treated author	Bad and Innocent Actors		
	Bad only	Innocent only	Bad and Innocent
	(1)	(2)	(3)
Bad Actor*Treated*Post(t>=1)			-0.411***
			(0.110)
Bad Actor*Author Standing*Treated*Post(t>=1)			-0.054
			(0.139)
Treated*Post(t>=1)	-0.122**	0.148**	0.248***
	(0.058)	(0.065)	(0.063)
Author Standing*Treated*Post(t>=1)	0.094	0.042	0.143
	(0.070)	(0.037)	(0.129)
Author-Paper Fixed Effects	Y	Y	Y
Year Since Publication Dummies	Y	Y	Y
Observations	32,258	20,617	52,875
Number of unique papers	1,865	1,503	3,368

Notes: This table considers all cases where an author has multiple retractions and where there is a single common author across these retractions; we define this author as "bad" and the other authors on the retracted papers as "innocent". Timing refers to year of first retraction. Author standing refers to the h-index for a treated author in the year prior to retraction, standardized by sample mean and standard deviation. All regressions report coefficients from maximum likelihood estimation of a Poisson count model, errors clustered by each retraction event. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.