# Gender differences in online visibility of early career researchers

## Introduction

Social media has greatly changed the way people interact with each other. It has substantially affected how scholars promote their research [6, 33]. Over the past decades, Twitter, Facebook, LinkedIn, and other social media platforms have been widely leveraged by researchers and the public to share and access scholarly materials within professional academic communities as well as informal social circumstances [6]. 70-80% of researchers have used a social media platform at least once to support their academic activities [32, 35]. Sharing and distributing scientific findings through social media help scholars gain online visibility for their research [17]. More online exposure not only increases the chances of the research being noticed, used, and has an impact but also helps grow the researchers' reputation and future career opportunities [6, 36]. Among the various social media, Twitter has been recognized as the most common platform for researchers to spread scientific information for online visibility [24, 16, 27]. It is especially used for mentioning scientific papers. Articles posted on Twitter, known as scholarly tweets [14], normally include external URLs, Digital Object Identifiers (DOIs), and article titles which facilitate that these articles can be easily found and shared.

Early-career researchers are an important group of the academic society [5, 4, 20], and they also mark the future of this society [3]. Getting published is just their first step in developing an academic career. Sharing and distributing their findings to generate visibility can maximize their scientific impact. Traditional promotion strategies, like attending conferences and workshops are usually costly, time-consuming, and less accessible for early-career researchers [37, 39]. In this growing digital world, online presence has become particularly important and is also an efficient way for young researchers to distribute their research to a broader community. The extensive interaction with the scientific community and the public could lead to a growing impact network for early-career researchers, which is essential for a long-term career in academia. Despite the increasing discussion on the role of social media in the visibility of researchers and their scientific work [6, 24, 39, 37, 30], only a few studies have paid attention to the online visibility of early-career researchers and the further consequences on these researchers' careers and impact [17]. Hence, it is of critical importance to gain more insights into this aspect.

Disparities exist in various aspects of science, including a lack of visibility for under-represented groups of researchers [22, 31, 11, 37, 23]. The scientific contributions of female researchers, has shown to be less cited and undervalued compared to those of their male counterparts [12, 37, 34], which leads to female scientists gaining less visibility in both academia and among the public. Such conscious or unconscious gender biases against women could in turn influence the career promotion and success of female researchers [15].

The emergence of social media has the potential to serve an important role in the movement toward increased equity, diversity, and inclusion within academia as it provides a widely available and readily accessible platform to scholars, including underrepresented groups [39]. Disseminating scientific findings through social media and breaking free from the constraints of space to aggregate mentions from vast audiences may help to democratize the evaluation of scholarly output, thus reducing the gender bias in academia and progressing to a more gender-balanced portrait [15]. Despite this potential for equalizing engagement, several evidence has indicated that social inequalities can be reproduced online where female researchers usually generate less visibility than their male counterparts [29, 37]. One of the explanations behind the less attention to the research by female scholars is that women are significantly less likely than men to self-promote their papers [37, 30], partly due to the "feminine modesty effect"[1]. Gaining visibility for one's work early on is important for researchers since such cumulative advantages can help broaden their recognition and build their professional network. However, whether the gender gaps are visible already within the early stages of an academic career, and whether less online visibility is in line with the lower probability of self-promotion among early-career female researchers are not well understood.

One of the most straightforward and observed consequences driven by the dissemination of scientific papers on social media is the citation. Gaining high citation scores is a particularly important step for a scholar to be recognized as a credible researcher and become visible as an expert in a research field [17]. It has been widely acknowledged that higher online visibility has a positive impact on the citations, especially pointing to a significant correlation between the scholarly tweets and the paper's citations [13, 9, 10]. Compared with being mentioned by others, publicizing one's own scientific papers is a more efficient way to draw attention from targeted readers, especially from scholars in related fields. Given this, it is worthwhile to investigate whether any additional advantages of self-promotion exist in the citations for the researchers, who act as the first-generation disseminators of their research findings. More importantly, whether self-promotion has the same benefit for female and male researchers when stepping into their academic careers, thus alleviating the subsequent cumulative gender differences, has received limited attention.

This paper aims to focus on the online attention paid to early-career researchers' scientific output as well as these researchers' self-promotion behaviors and address some unanswered questions: (1) Are there any gender differences in the Twitter mentions on the first publications of early-career researchers and the mention counts? (2) Are there any gender differences in the probability of early-career researchers self-promoting their first publications? (3) Can self-promotion bring additional benefits for early-career researchers in their late academic careers, compared with general online mentions on Twitter? Does a gender gap exist in the benefits of citations?

# Materials and Methods

## Early-career researchers and their first publications

This study uses large-scale bibliometric data from Scopus to identify all authors who started publishing during the period 2012–2016. The starting year of publication is used to define the academic cohort of researchers. We consider the researchers who are in their first three years since the first publication i.e., years one, two, and three, to identify the early-career researchers. In most fields of science, it is acknowledged that the first author contributes the most to the work, by undertaking most of the research and writing most of the paper [21, 2, 26, 28]. Based on this, we further select those who have published at least one first-authored paper in their early-career stage, that is, the first three years of their career. Then we look at the online visibility of a researcher's first *first-authored publication* which marks the start of a researcher's academic career in the form of scientific publications. Thereafter, we simplify the first *first-authored publication* as the first publication to make it more concise.

Our analysis on the online visibility of early-career researchers looks at online mention and self-promotion of their first publication on Twitter, proceeding in the following steps: (1) we first look at the gender differences in the probability of one's first publication being mentioned on Twitter and estimate the tweet counts received on the first publications by early-career female and male researchers if they are mentioned. (2) we then turn attention to the gender differences in the probability of self-promotion on Twitter and examine whether there is a gender difference in the process; (3) we examine the subsequent impact of this self-promotion on the citations of their first publication by comparing the impact of overall online mentions on citations.

## Online mentions on Twitter

We utilize the Altmetric Details Page API to retrieve the online mentions on their first publication on Twitter. Twitter mentions as tracked by Altmetric include all tweets (original), retweets, and quoted tweets that contain a direct link to a scholarly output. Here we only consider the original tweets to investigate the online visibility of researchers.

We observed a sheer number (over two-thirds) of first publications by early-career researchers receiving no online mentions, and there is an over-dispersion of publications being mentioned only once. To accommodate the excess zeros and over-dispersion of Twitter mention counts, we used a zero-inflated negative binominal (ZINB) regression to model the online visibility of early career researchers' first publication and then to examine whether it differs by gender [38]. Furthermore, we incorporate the random effects of country variability in the intercept and the slope of gender to consider the fact that the received Twitter mentions may vary by the researcher's country of affiliation.

In addition to the variable of interest, i.e., gender, we also consider these control variables: author's cohort (2012 is the reference level), the field of specialty (without a discipline assignment is the reference level), the number of authors in the first publication, academic age which is the relative publication year since their first publication (1, 2, or 3, and 1 is the reference level), the ranking quantile of the published journal in the subject area (journal rank of Q4 is the reference level), and whether the publication is a product of international collaboration and whether it has collaborated with other universities/institutes. We also included interactions between gender and other control variables in the model. See SI Appendix, for more details about the mixed-effect ZINB model for online mentions.

## Self-promotion on Twitter

Due to licensing restrictions from Twitter, Altmetric only provides the Tweet ID and User ID (individual tweeter ID) in their Details Page API, lacking the individual information of the tweeter. That means, we can only see whether the publication has been tweeted or not through the publication's DOI, but with no clues to identify who tweeted it. We further employ Twitter's public API to track more details about the tweeters including their display names and handle names (i.e., username or @name, which is unique to Twitter), using User ID (Twitter's ID for an individual tweeter) we obtained from Altmetric. We judged whether the early-career researchers had self-promoted their first publication by comparing their names retrieved from Scopus with the names of the tweeters who mentioned the publication on Twitter. The name-matching process we elaborated to find the self-promoted researchers not only includes the display name and handle name corresponding to each Twitter ID but also incorporates an existing open data set of scholars on Twitter (e.g., *OpenAlex Database* containing their names and Twitter IDs, [25]. See SI Appendix for more details about identifying self-promoted researchers.

After identifying the self-promoted publications, we employed logistic regression to model the probability of self-promotion for the researcher and examine the potential gender differences in this process. In addition to the control variables we mentioned above, we also considered whether their publication has received mentions on Twitter (not being tweeted is the reference level) and the counts of tweets by others. We discuss more details in the the mixed-effect logistic model of self-promotion among early-career researchers in SI Appendix.

## Impact of Twitter mentions on citations

To explore the impacts arising from general Twitter mentions and early-career researchers' self-promotion on the citations of their first publications, we first used propensity score matching (*PSM*) to match the early-career researchers who received Twitter mentions on their first publications with those who did not. As factors in the matching process, we considered gender, academic cohort, discipline, the journal rank of their first publication, affiliated country, the number of authors, and whether the publication is a product of an international collaboration to estimate the propensity score of getting Twitter mentions using a logistic model. We further confined each pair of researchers who have the same gender, are from the same cohort, do research in the same field of specialty, and publish their first article in the journals ranking at the same quantile, to generate the first matching of paired researchers (*Matching 1*). Assuming the significant impact of online visibility on researchers' publications, we further investigated whether self-promotion among early-career researchers can bring additional benefits. Similarly, we employed *PSM* to match those who self-promoted their first publication with those who did not (that means, their publication was only being mentioned by others) from the pool of researchers whose first publication has been mentioned on Twitter. In addition to the factors we considered above in the logistic model of *PSM*, we add the Tweet counts as the control variable to estimate the propensity score of self-promotion, ensuring a similar level of online exposure on Twitter. We finally generate the second matching of self-promoted researchers paired with those who did not (*Matching 2*).

To analyze whether online mentions, as well as self-promotion, play a different role in the discipline-normalized annual citation scores of early-career researchers' first publications within five years after publication (see SI Appendix for the definition and calculation) by gender, we employed a gamma regression to estimate the relationship between online visibility and the cumulative normalized citations for the matched researchers in (*Matching 1*) since the citation scores show a right-skewed pattern. In addition to the treatment, that is, whether the researcher's first publication is mentioned on Twitter (0/1), we also included in the model each early-career researcher's gender, cohort, discipline, the journal rank of the first publication, the number of authors, and whether the publication is a product of international collaboration as control variables and their interaction with the treatment. This model helps us further measure the marginal effects of online mentions on the citation (e.g., the citation difference between the publications with online mentions and those without online mentions) for both female and male researchers.

To estimate the marginal effect of self-promotion on citations by gender, we used a similar gamma regression model with the treatment of self-promotion (0/1) and the control variables mentioned above plus the number of Twitter mentions in the researchers' population of (*Matching 2*). The interaction between treatment and control variables is also included in the model.

# Results

We obtained 567,162 published researchers who are from the cohort of 2012–2016 and have published at least a paper in Scopus-indexed outlets as first authors within the first three years of their academic career (i.e., for the cohort 2012, the first-authored publication should be during the period 2012–2014). Among these early-career researchers, 161,884 (28.54%) were detected to receive Twitter mentions on their first publication, and 8,677 (1.53%) researchers promoted their first publication themselves (self-promoted). By using a systematic process composed of name-gender detection methods [40] and a category of six macro research fields of specialty, we identified the genders and disciplines of these researchers. Specifically, 71,660 female researchers (32.75% of all published female authors) received Twitter mentions on their first publications while 90,224 male researchers (25.90% of all published male authors) received mentions. The aggregated results indicate that early-career female researchers are more likely to get mentions online. More details on the descriptive statistics on the sample and self-promotion rates are shown in SI Appendix, Table. 1.

Based on the multilevel ZINB model that controls the inflated zero mentions and over-dispersion of being mentioned only once per publication, we find that even though early-career female researchers are more likely to gain more attention on Twitter, they are still at a disadvantage on average in the mention counts relative to male researchers (see Model 7, SI Appendix Table. 3 for full regression result of the multilevel ZINB model as well as the step-wise process from the model 0 that only controls gender (model 1) to model 7). Fig. 1 further predicts how many mentions are received by female and male researchers given the existence of online mentions, and further measures the marginal effects of gender in Twitter attention (the value and significance of the difference shown on the top of each category). By disaggregating into different factors, the gender difference in the counts of Twitter mentions displays a mixed pattern. While for the researchers from earlier cohorts (2012, 2013, and 2014), males were gaining more mentions, since the cohort of 2015, female researchers tended to receive more attention online, and the gender gaps became smaller. The field of specialty also determines the counts of online mentions and the gender difference in this process. Male researchers in the field of Social Sciences are predicted to receive the most Twitter mentions (1.8) on average, significantly more than their female counterparts (1.5). This result is in line with the previous finding of a higher presence of researchers from Social Sciences and Humanities in Altmetrics and Twitter than the Natural Sciences researchers [19, 7]. However, in Engineering and Technology, which is always dominated by male researchers in terms of population size [40], the first publications by female early-career researchers are predicted to receive more attention online with a marginal effect of 0.03. The striking finding to some extent demonstrated that female researchers do an equally good job in the traditional male-dominated disciplines, which attracted more attention from the online audience.

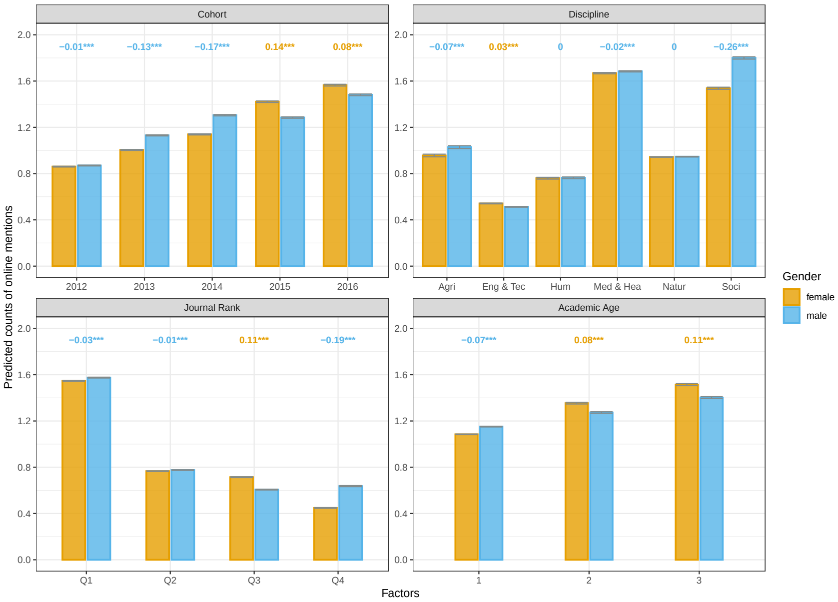


Figure 1: Predicted number of Twitter mentions on early-career female and male researchers' first publication, by cohort, discipline, journal rank, and academic age. The numbers on the top show the marginal effects of gender with statistical significance.

When looking at the probability of self-promotion, Fig. 2 depicts a different pattern relative to the general online mentions shown above. Across all categories, male researchers always have a higher probability of self-promoting their first publication. With cohort, the probability of self-promotion among both female and male early-career researchers has increased, and the smallest gender difference is observed in the most recent cohort. Disaggregating by six macro fields of specialty, the marginal effects of gender on the probability of self-promotion are larger for those working in Social Sciences (1.45%) and Humanities (0.60%) compared to those in Engineering and Technology (0.06%). Overall levels of self-promotion are also higher in the Social Sciences across both genders compared with STEM fields. The highest rate of self-promotion in the Social Sciences echos the largest number of online mentions in this field, while in the Medical and Health Sciences where both female and male researchers on average received over 1.5 mentions online, the probability of self-promotion in this field is below 2%, smaller than the researchers in Social Sciences and Humanities. We can also see that male researchers are more likely to promote their first paper when the paper was published in a Q1 (top 25%) journal which has the largest gender gap (0.59%). We finally compared the probability of self-promotion and the gender difference when accounting for academic age, which means the year since their first publications. The gender gap in self-promotion gradually increased from 0.41% to 0.5%, from the first year of their career to the third year. Such a widening gap in the willingness to self-promote would benefit male researchers in the long run with cumulative attention.

To further probe into the longer-term effects of online mentions and self-promotion behavior on scientific influence in terms of the citation of early career researchers' first publications, we created two matched groups of scholars by considering multiple variables (see a description in the Methods section). The first matching (Matching 1) is composed of 135,562 pairs (271,124 individuals), where the treated group in Matching 1 is those who received Twitter mention(s) on their first publications and the control group is those who did not. In another matching (Matching 2), 6,189 pairs (12,378 individuals) are included. The treated group here is those who self-promoted their

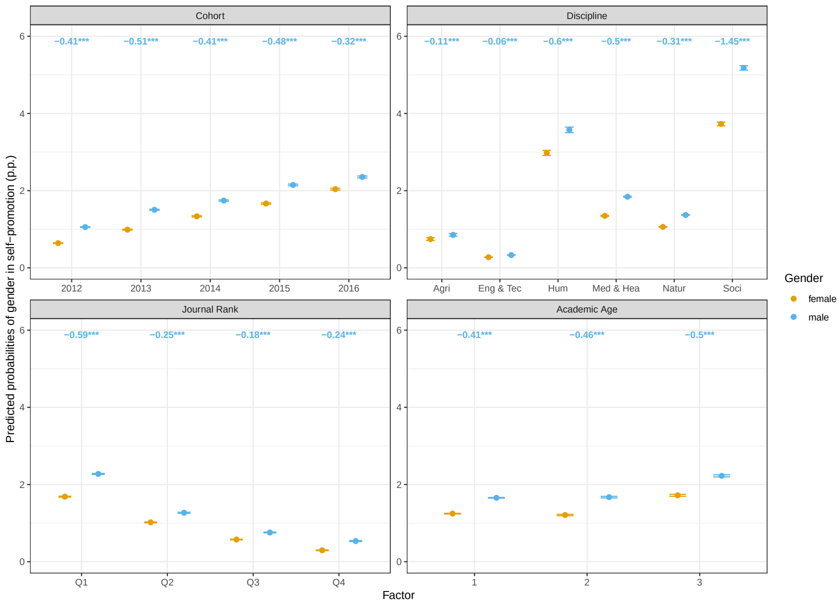


Figure 2: Predicted probabilities of early-career female and male researchers self-promoting their first publication, by cohort, discipline, journal rank, and academic age. The numbers on the top show the marginal effects of gender with statistical significance.

first publications in addition to others' mention(s). The control group is those who only received others' mention(s). The comparison between the results in Matching 1 and Matching 2 helps us investigate whether there is an additional advantage in citation performance from self-promotion. We use the discipline-normalized annual citation scores in the first five years since publication to measure the citations of early-career researchers' first publications. It is compared with the average citation level of all first publications by early-career researchers in the same discipline and the same publishing year (see more details about the normalization process in SI Appendix).

Fig. 3 shows the marginal effects of Twitter mentions on female and male researchers' first publications, which can be interpreted as the difference in the predicted discipline-normalized citation received by the treated researchers versus the controlled researchers. In terms of the general online mentions, both early-career female and male researchers benefit from the online dissemination on Twitter in the five-year normalized citation scores of their first publications. However, female researchers always gain more citations as a result of being mentioned online, for both the overall effect and the disaggregated effect after controlling for other factors including cohort, discipline, journal rank, and academic age. The marginal effects of online mentions on citation scores indicate a slightly increasing trend by cohort, that means, researchers from the recent cohorts tend to gain more citations on their first publications if being mentioned on Twitter. On the other side, the gender gaps in the citation gains tend to be gradually reduced with cohort, with the smallest gaps for the researchers from cohort 2016. In addition, the interaction between the Twitter mentions and the research field also determines to which extent more citations would be accumulated. The researchers from Medical and Health Sciences tend to gain the most additional citation scores, increasing by 0.4 on the average citations of all first publications by early-career researchers with the same background. The field of Social Sciences, which is most likely to have mentions on Twitter (Table. 1 in SI Appendix) saw an increase of 0.35 citation scores in the first publications of both early-career female and male researchers. Other research fields, on the contrary, indicate relatively smaller gains in the five-year citation scores for early-career researchers. Especially for the male researchers from the Humanities, there are no significant gains in their first publication's citation scores. Besides, online mentions benefit early-career female researchers publishing in Q1 journals with around 0.05 more citation scores compared to their male counterparts.

Given the first publications of early-career researchers getting mentions on Twitter, Fig. 4 (based on Matching 2 results) shows that self-promotion is associated with higher citations received

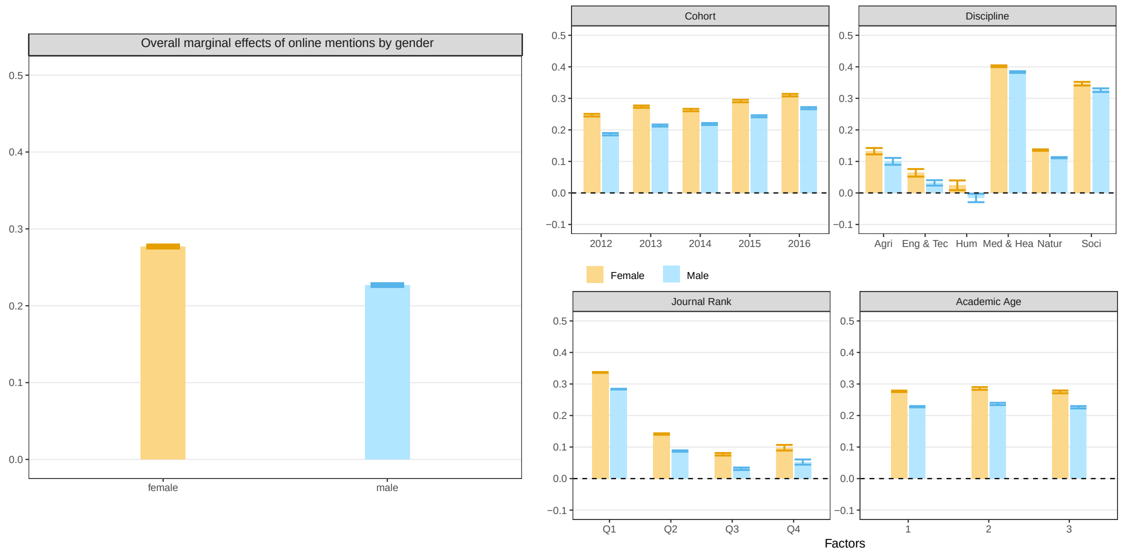


Figure 3: Marginal effects of Twitter mentions in the 5-year cumulative citations (discipline-normalized by publishing year) among early-career female and male researchers (Matching 1), at the overall level (left) and disaggregated by cohort, discipline, and the journal rank (right).

compared to those only mentioned on Twitter by others. In the overall trend (left panel) and in the disaggregated view (right panel) for all controlled factors, male researchers received higher citations with self-promotion. Only the effect of self-promotion on the first publications of early-career female researchers during their second academic year is not statistically significant. As online mentions play an increasingly important role in accumulating citations, self-triggered citations, on the flip side, have been weakening with cohort, decreasing normalized citation gains by 0.25 units from the cohort of 2012 to 2016. Self-promotion on Twitter generated more citation scores for the first publications by male researchers. That suggests, despite Twitter mentions helping more to increase the citations of female researchers' first publications, such advantages can be offset if male researchers promote their first publication, especially given the fact that early-career male researchers are more likely to self-promote their first publications. The largest gender gaps can be seen in the field of Medical and Health Sciences, and also for the publications in the Q1 journals, where male researchers are way ahead by nearly 0.2 discipline-normalized citation scores compared with their female counterparts. Another interesting finding is that the early-career researchers from the Agricultural Sciences field would gain the highest self-triggered citations while their gains from the Tweet mentions relative to those without any mentions are comparatively smaller than those from the fields of Humanities and Social Sciences.

## Discussion

The widespread availability of social media has significantly changed scholarly communication, not only enabling scientific work to receive immediate attention from various fields but also helping researchers promote their research in a faster and easier way. Twitter has been seen as the most important gathering place on social media for academics. The usage of Twitter in scholarly communication could greatly benefit two groups of researchers: the early-career scholars who demand more opportunities for sharing their research and connecting with other scholars to establish professional networks and generate impacts from early stages; underrepresented researchers, such as females, who can make use of the more available, readily accessible digital tools to break free some constraints and barriers in the real world and engage in a more diverse and inclusive communication environment. The paper correlates the early career stages with gender inequality in academia to examine whether there are gender differences in the online visibility of early-career researchers and how the interaction between gender and online visibility makes a difference in the

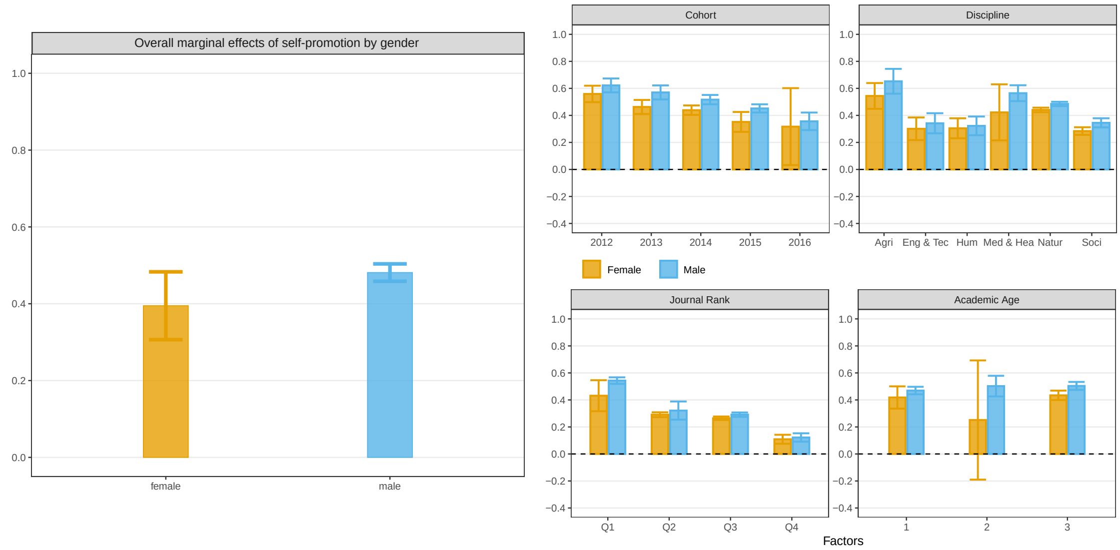


Figure 4: Marginal effects of self-promotion on Twitter in the 5-year cumulative citations (discipline-normalized by publishing year) among early-career female and male researchers (Matching 2), at the overall level (left) and disaggregated by cohort, discipline, and the journal rank (right).

longer-term academic impact and citations.

One of the reasons why Twitter was engrossing for researchers is that it not only creates an equitably accessible platform for scientific knowledge to be disseminated, but it also allows the researchers to participate in promoting their research to increase the probability of it being noticed, used and cited. We untangle the self-promotion behaviors from all the online attention on Twitter to test for the gender difference in the self-triggered Twitter mentions and its role in accumulating the scientific impacts, compared to the general Twitter mentions.

Social media to some extent paves the way for female researchers to increase their online visibility at the early career stage. Females have more chances of receiving online mentions, even though they are more likely to be mentioned only once for their first publications. However, Social Sciences which has the highest social media presence of Twitter mentions per publication, shows the biggest gender difference in that male researchers' publications tend to gather more mentions on average. There is also a gender gap in self-promotion. Early-career women are less inclined to self-promote their publications than men, whatever the cohort they are from, the research area they work in, and the ranking of the journal they publish in. It suggests the "feminist modesty effect" has been rooted in the junior female researchers already.

Higher social media exposure to articles rewards early-career researchers with higher citation scores. The follow-up effects of Twitter mentions benefit female researchers more with a higher increase in the citations of their first publications, compared to those of males' first publications. However, we observe that there is an additional advantage in citation performance from self-promotion. It suggests a process of cumulative disadvantage starting early in scientific careers: men are more likely to self-promote their first publication, with subsequent citation impacts also being larger for men. This negative feedback loop could lead to exacerbating already existing gender inequalities in academia.

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# Appendix

## Methods

### Self-promotion identification

Although users were not actually required to use their real names in their Twitter display names or handle names, we believe that the majority of researchers use their real names on Twitter given the promotion purpose, with a stronger focus on facilitating social networking [18]. Author-name matching is also the dominant method to identify researchers on Twitter [8, 18]. In addition, the provided real name of each researcher also comes in various combinations of first name, initials, last name, middle name, and titles. For each early-career researcher in our dataset, we firstly combine their first names and last names that were retrieved from Scopus, with or without space, to form the four combinations as the possible author names, shown in our name-matching process in Fig. 5. We collected all User IDs of those who mentioned the first publication of each early-career researcher, and we further acquired both display names and handle names of the tweeters by entering Twitter IDs in Twitter API. In addition, we also consider an open data set of scholars on Twitter (e.g., *OpenAlex Database*) which includes 423,920 unique tweeter IDs forming 498,672 unique author-tweeter pairs, by tracking the information from OpenAlex and Crossref Event Data [25]. We then compare each category of Twitter names with the four combinations of author names to calculate the similarity scores and find the best-matched name with the highest similarity score for each category. We decided on the final best-matched Twitter name from the three matched names and determined if the author self-promoted their first publication only if the match score for the best-matched name exceeds 0.6.

### Multilevel ZINB model for measuring online mentions on Twitter

We assume that the counts of Twitter mentions for each early-career researcher's first publication reflect two different processes: First, either other Twitter users saw the publication and decided to post it on Twitter, or the researchers promoted their papers on Twitter. Both of these processes help the publication become visible online. Second, the publication can accumulate more mentions over time. Hence, to accommodate the excess zeros and over-dispersion of Twitter mention counts, we used a zero-inflated negative binominal (ZINB) regression to model the online visibility of early career researchers' first publication and then examine whether it differs by gender. A ZINB consists of two parts: a logistic component to predict the probability of *certain zero* mentions, and a negative binomial component to model the mention counts if being mentioned (Eq. (1))).
$\pi_i$ is the logistic link function which indicates the probabilities of excess zero mentions online for researcher $i$ (Eq. (2)). In addition to the variable of interest, i.e. gender ($gender_i$), we also consider these control variables: author's cohort (2012 is the reference level), the field of specialty (without a discipline assignment is the reference level), the number of authors in the first publication, the relative publication year since the academic career (1, 2, or 3, and 1 is the reference level), the ranking quantile of the published journal in the subject area (journal rank of Q4 is the reference level), and whether the publication is a product of international collaboration and whether it is the result of a collaboration with other universities/institutes (i.e., multiple institutions are involved). We also included interactions between gender and other control variables in the model. For the negative binomial component $g(M_{ij})$, we applied the same control variables as well as their interactions with gender in $\mu_{ij}$ to model the probability of receiving $n$ times Twitter mentions for the researcher $i$ (Eq. (3)).

$$P(M_i = n) = \begin{cases} \pi_i + (1-\pi_i) \times g(M_i), & \text{if } n = 0 \\ (1-\pi_i) \times g(M_i), & \text{if } n > 0 \end{cases}$$
$$g(M_i) = \Pr(Y = M_i | \mu_i, p) \tag{1}$$

$$logit(\pi_i) = \gamma_0 + \gamma_{gender} \times gender_i + \gamma_{cov_k} \times cov_{k,i} + \gamma_{gender \times cov_k} \times gender_i \times cov_{k,i} \tag{2}$$

$$ln(\mu_i) = \beta_0 + \beta_{gender} \times gender_i + \beta_{cov_k} \times cov_{k,i} + \beta_{gender \times cov_k} \times gender_i \times cov_{k,i} \quad (3)$$

Considering that the received Twitter mentions may vary by the researcher $i$'s affiliation country $j$, we extend the models in Eq. (2) and Eq. (3) to a mixed-effects version by incorporating the random effects for country variability in the intercept and the slope of gender in Eq. (4) and Eq. (5), respectively.

$$\begin{aligned} logit(\pi_{ij}) = \gamma_0 + \delta_{0,j} + (\gamma_{gender} + \delta_{gender,j}) \times gender_{ij} + (\gamma_{cov_k} + \delta_{cov_k,j}) \times cov_{k,ij} \\ + (\gamma_{gender \times cov_k} + \delta_{gender \times cov_{k,j}}) \times gender_{ij} \times cov_{k,ij} \end{aligned} \quad (4)$$

$$\begin{aligned} ln\mu_{ij} = \beta_0 + \alpha_{0,j} + (\beta_{gender} + \alpha_{gender,j}) \times gender_{ij} + (\beta_{cov_k} + \alpha_{cov_k,j}) \times cov_{k,ij} \\ + (\beta_{gender \times cov_k} + \alpha_{gender \times cov_{k,j}}) \times gender_{ij} \times cov_{k,ij} \end{aligned} \quad (5)$$

Before considering all of the control variables and the country-level random effects in Eq. (4) and Eq. (5) to generate the full ZINB model, we take a step-wise method by gradually adding control variables in the basic model (*Model 0*) only with the variable of gender. And the result of step-wise modeling online mentions is shown in Table. 3.

According to the estimated results, we predict the counts of Twitter mentions on the first publications of early-career female and male researchers, and measure the marginal effects of gender (gender gap, i.e. difference between male and female researchers) in this process.

**Logistic model for measuring self-promotion on Twitter**

Similar to modeling online mentions, we employed logistic regression to model the probability of self-promotion for the researcher $i$ and examine the potential gender differences in this process. In addition to the control variables we mentioned before, we also considered whether their publication has received mentions on Twitter (not being tweeted is the reference level) and the counts of tweets by others. The mixed-effects version is shown as follows:

$$\begin{aligned} logit(P(self_{ij} = 1)) = \theta_0 + \eta_{0,ij} + (\theta_{gender} + \eta_{gender,j}) \times gender_{ij} + (\theta_{cov_k} + \eta_{cov_k,j}) \times cov_{k,ij} \\ (\theta_{gender \times cov_k} + \eta_{gender \times cov_{k,j}}) \times gender_{ij} \times cov_{k,ij} \end{aligned} \quad (6)$$

Similarly, we also employ the step-wise method by gradually adding control variables in the basic model (*Model 0*) only with the variable of gender. The result of step-wise modeling self-promotion is shown in Table. 4.

According to the estimated results, we predict the probability of self-promotion of early-career female and male researchers, and measure the marginal effects of gender (gender gap, i.e. difference between male and female researchers) in this process.

**Disciplinary-normalized annual citation scores of publications by early career researchers**

We normalize the citation counts by discipline and publishing year to make it more comparable with people in the same research field. Considering the impacts from different levels of experience, we divide the actual citation of each publication by all early career researchers' first publications in the same discipline and publishing year as the citation scores and accumulate the citation scores for the first 5 years since publication. The measurement of five-year normalized citation impacts for each first publication in the discipline $f$ and the publishing year $t$ is represented as below, where $e_{ft}$ means the average (expected) citation counts for the early-career researchers' first publications:

$$DNC = \sum_{t}^{t+4} \frac{c}{e_{ft}} \quad (7)$$

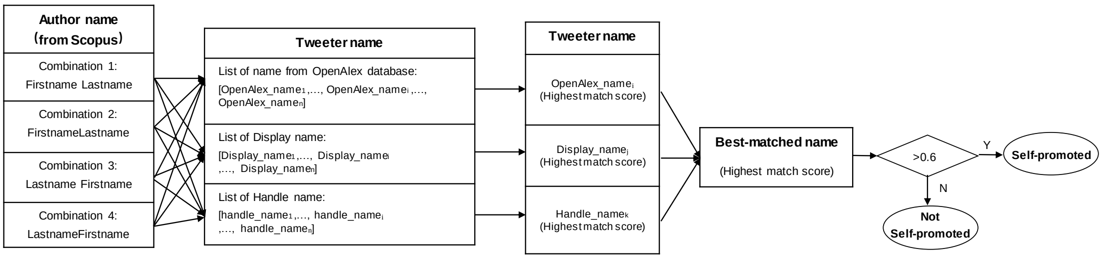


Figure 5: The workflow of matching Scopus-published researchers and Tweeters

Table 1: The count and percentage of the published researchers (third and fourth columns) and those who received Twitter mentions (fifth and sixth columns) and self-promoted their first publication (seventh and eighth columns) by cohort (2012-2016), gender, and discipline.

| | | **Number of newly-published authors** | | **Number of online mentioned authors** (% among published authors) | | **Number of self-promoted authors** (% among published authors) | |
|---|---|---|---|---|---|---|---|
| **Cohort** | **Discipline** | **Female** | **Male** | **Female** | **Male** | **Female** | **Male** |
| 2012 | Agricultural Sciences | 1320 | 1484 | 277 (20.98%) | 184 (12.40%) | 5 (0.38%) | 2 (0.13%) |
| | Engineering and Technology | 2650 | 8287 | 125 (4.72%) | 292 (3.52%) | 7 (0.26%) | 17 (0.21%) |
| | Humanities | 1135 | 1495 | 194 (17.09%) | 233 (15.59%) | 25 (2.20%) | 32 (2.14%) |
| | Medical and Health Sciences | 18695 | 20618 | 6365 (34.05%) | 6033 (29.26%) | 144 (0.77%) | 188 (0.91%) |
| | Natural Sciences | 19672 | 38346 | 3770 (19.16%) | 6369 (16.61%) | 87 (0.44%) | 322 (0.84%) |
| | Social Sciences | 4391 | 4754 | 1355 (30.86%) | 1192 (25.07%) | 87 (1.98%) | 145 (3.05%) |
| | No discipline assigned | 86 | 154 | 22 (25.58%) | 35 (22.73%) | 1 (1.16%) | 1 (0.65%) |
| | **Total** | 47949 | 75138 | 12108 (25.25%) | 14338 (19.08%) | 356 (0.74%) | 707 (0.94%) |
| 2013 | Agricultural Sciences | 1385 | 1409 | 317 (22.89%) | 253 (17.96%) | 8 (0.58%) | 11 (0.78%) |
| | Engineering and Technology | 2800 | 8481 | 162 (5.79%) | 432 (5.09%) | 7 (0.25%) | 20 (0.24%) |
| | Humanities | 1126 | 1522 | 199 (17.67%) | 273 (17.94%) | 16 (1.42%) | 37 (2.43%) |
| | Medical and Health Sciences | 18441 | 20972 | 7393 (40.09%) | 7177 (34.22%) | 195 (1.06%) | 325 (1.55%) |
| | Natural Sciences | 19274 | 37207 | 4676 (24.26%) | 7642 (20.54%) | 177 (0.92%) | 404 (1.09%) |
| | Social Sciences | 4083 | 4586 | 1336 (32.72%) | 1375 (29.98%) | 132 (3.23%) | 206 (4.49%) |
| | No discipline assigned | 143 | 267 | 29 (20.28%) | 32 (11.99%) | 0 (0.00%) | 3 (1.12%) |
| | **Total** | 47252 | 74444 | 14112 (29.87%) | 17184 (23.08%) | 535 (1.13%) | 1006 (1.35%) |
| 2014 | Agricultural Sciences | 1140 | 1256 | 301 (26.40%) | 283 (22.53%) | 9 (0.79%) | 7 (0.56%) |
| | Engineering and Technology | 2794 | 8603 | 209 (7.48%) | 486 (5.65%) | 6 (0.21%) | 30 (0.35%) |
| | Humanities | 1048 | 1419 | 229 (21.85%) | 293 (20.65%) | 32 (3.05%) | 44 (3.10%) |
| | Medical and Health Sciences | 16707 | 19907 | 7550 (45.19%) | 7926 (39.82%) | 263 (1.57%) | 335 (1.68%) |
| | Natural Sciences | 17956 | 34823 | 5193 (28.92%) | 8732 (25.08%) | 206 (1.15%) | 469 (1.35%) |
| | Social Sciences | 3944 | 4156 | 1425 (36.13%) | 1335 (32.12%) | 158 (4.01%) | 210 (5.05%) |
| | No discipline assigned | 95 | 173 | 26 (27.37%) | 53 (30.64%) | 3 (3.16%) | 2 (1.16%) |
| | **Total** | 43684 | 70337 | 14933 (34.18%) | 19108 (27.17%) | 677 (1.55%) | 1097 (1.56%) |
| 2015 | Agricultural Sciences | 1038 | 1186 | 306 (29.48%) | 292 (24.62%) | 8 (0.77%) | 17 (1.43%) |
| | Engineering and Technology | 3020 | 8562 | 237 (7.85%) | 590 (6.89%) | 8 (0.26%) | 30 (0.35%) |
| | Humanities | 1017 | 1298 | 239 (23.50%) | 317 (24.42%) | 46 (4.52%) | 66 (5.08%) |
| | Medical and Health Sciences | 15363 | 18273 | 7540 (49.08%) | 8145 (44.57%) | 293 (1.91%) | 402 (2.20%) |
| | Natural Sciences | 16264 | 31686 | 5288 (32.51%) | 8943 (28.22%) | 241 (1.48%) | 492 (1.55%) |
| | Social Sciences | 3760 | 4108 | 1469 (39.07%) | 1365 (33.23%) | 196 (5.21%) | 238 (5.79%) |
| | No discipline assigned | 112 | 194 | 38 (33.93%) | 62 (31.96%) | 1 (0.89%) | 1 (0.52%) |
| | **Total** | 40574 | 65307 | 15117 (37.26%) | 19714 (30.19%) | 793 (1.95%) | 1246 (1.91%) |
| 2016 | Agricultural Sciences | 1065 | 1175 | 335 (31.46%) | 278 (23.66%) | 21 (1.97%) | 11 (0.94%) |
| | Engineering and Technology | 3063 | 8645 | 298 (9.73%) | 634 (7.33%) | 11 (0.36%) | 43 (0.50%) |
| | Humanities | 992 | 1276 | 265 (26.71%) | 304 (23.82%) | 44 (4.44%) | 67 (5.25%) |
| | Medical and Health Sciences | 14625 | 17556 | 7399 (50.59%) | 7956 (45.32%) | 359 (2.45%) | 371 (2.11%) |
| | Natural Sciences | 16050 | 30565 | 5611 (34.96%) | 9192 (30.07%) | 306 (1.91%) | 571 (1.87%) |
| | Social Sciences | 3390 | 3632 | 1413 (41.68%) | 1424 (39.21%) | 195 (5.75%) | 250 (6.88%) |
| | No discipline assigned | 178 | 265 | 69 (38.76%) | 92 (34.72%) | 0 (0.00%) | 11 (4.15%) |
| | **Total** | 39363 | 63114 | 15390 (39.10%) | 19880 (31.50%) | 936 (2.38%) | 1324 (2.10%) |
| **Total** | | **218822** | **348340** | **71660 (32.75%)** | **90224 (25.90%)** | **3290 (1.51%)** | **5380 (1.54%)** |

Table 2: Regression results of the Odds Ratios (OR) of *receiving zero mentions* on Twitter. Control variables are gradually added from Model 0 with only gender to Model 6. Model 7 considers the random effects of countries of affiliation authors based on Model 6.

**Results of model comparison**

| | **Model 0** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** | **Model 7** |
|---|---|---|---|---|---|---|---|---|
| ***Predictors*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** |
| Intercept | $0.09^{***}$ | $0.69^{***}$ | $1.44^{**}$ | $1.79^{***}$ | $2.19^{***}$ | $2.16^{***}$ | $2.19^{***}$ | $2.18^{***}$ |
| Gender [female] | 0.00 | 0.79 | 1.05 | $2.09^{***}$ | $1.85^{**}$ | $1.76^{**}$ | $1.87^{**}$ | 1.50 |
| | | | | | | | | |
| Discipline [Agri] | | 0.72 | $0.67^{**}$ | $0.68^{**}$ | $0.70^{**}$ | $0.69^{**}$ | $0.70^{**}$ | 0.85 |
| Discipline [Eng & Tech] | | $4.61^{***}$ | $4.54^{***}$ | $4.48^{***}$ | $4.65^{***}$ | $4.24^{***}$ | $4.25^{***}$ | $4.79^{***}$ |
| Discipline [Hum] | | $0.47^{***}$ | $0.39^{***}$ | $0.14^{***}$ | $0.15^{***}$ | $0.13^{***}$ | $0.14^{***}$ | $0.35^{***}$ |
| Discipline [Med & Hea] | | 0.00 | 0.00 | $0.09^{***}$ | $0.11^{***}$ | $0.10^{***}$ | $0.10^{***}$ | $0.15^{***}$ |
| Discipline [Natur] | | $0.37^{***}$ | $0.35^{***}$ | $0.41^{***}$ | $0.49^{***}$ | $0.48^{***}$ | $0.48^{***}$ | $0.56^{***}$ |
| Discipline [Soci] | | $0.29^{***}$ | $0.26^{***}$ | 0.19 | $0.20^{***}$ | $0.17^{***}$ | $0.17^{***}$ | $0.31^{***}$ |
| Gender [female]*Discipline [Agri] | | $0.40^{***}$ | $0.32^{***}$ | $0.41^{***}$ | $0.46^{***}$ | $0.48^{***}$ | $0.47^{***}$ | 0.81 |
| Gender [female]*Discipline [Eng & Tech] | | 0.93 | 0.96 | 0.91 | 0.86 | 0.88 | 0.87 | 0.89 |
| Gender [female]*Discipline [Hum] | | 1.12 | 1.05 | 0.82 | 0.86 | 0.98 | 0.98 | 1.22 |
| Gender [female]*Discipline [Med & Hea] | | 0.457 | 0.02 | $0.52^{***}$ | $0.53^{***}$ | $0.56^{***}$ | $0.57^{***}$ | 0.84 |
| Gender [female]*Discipline [Natur] | | $0.46^{***}$ | $0.54^{***}$ | $0.43^{***}$ | $0.51^{***}$ | $0.65^{**}$ | $0.66^{**}$ | 0.75 |
| Gender [female]*Discipline [Soci] | | 0.00 | $0.04^{**}$ | $0.35^{**}$ | $0.39^{***}$ | $0.41^{***}$ | $0.41^{***}$ | 0.68 |
| | | | | | | | | |
| Cohort [2013] | | | $0.74^{***}$ | $0.74^{***}$ | $0.76^{***}$ | $0.76^{***}$ | $0.76^{***}$ | $0.78^{***}$ |
| Cohort [2014] | | | $0.53^{***}$ | $0.53^{***}$ | $0.53^{***}$ | $0.54^{***}$ | $0.54^{***}$ | $0.50^{***}$ |
| Cohort [2015] | | | $0.34^{***}$ | $0.34^{***}$ | $0.32^{***}$ | $0.33^{***}$ | $0.34^{***}$ | $0.31^{***}$ |
| Cohort [2016] | | | $0.34^{***}$ | $0.36^{***}$ | $0.35^{***}$ | $0.37^{***}$ | $0.36^{***}$ | $0.31^{***}$ |
| Gender [female]*Cohort [2013] | | | $0.77^{**}$ | 1.05 | 0.96 | 0.88 | 0.89 | $0.85^{**}$ |
| Gender [female]*Cohort [2014] | | | $0.58^{***}$ | 1.07 | 0.96 | $0.84^{**}$ | $0.85^{**}$ | $0.80^{***}$ |
| Gender [female]*Cohort [2015] | | | 0.88 | $1.59^{***}$ | $1.46^{***}$ | $1.27^{***}$ | $1.29^{***}$ | $1.19^{**}$ |
| gender [female]*Cohort [2016] | | | $0.70^{***}$ | $1.49^{***}$ | $1.32^{***}$ | 1.12 | 1.15 | 1.13 |
| | | | | | | | | |
| Journal rank [Q1] | | | | $0.55^{***}$ | $0.54^{***}$ | $0.58^{***}$ | $0.59^{***}$ | $0.54^{***}$ |
| Journal rank [Q2] | | | | $1.67^{***}$ | $1.52^{***}$ | $1.54^{***}$ | $1.52^{***}$ | 1 |
| Journal rank [Q3] | | | | $6.31^{***}$ | $5.33^{***}$ | $5.17^{***}$ | $5.17^{***}$ | $2.92^{**}$ |
| Journal rank [Q4] | | | | $29.12^{***}$ | $24.36^{***}$ | $23.67^{***}$ | $23.67^{***}$ | $11.57^{***}$ |
| Gender [female]*Journal rank [Q1] | | | | $0.26^{***}$ | $0.32^{*}$ | $0.40^{**}$ | $0.39^{**}$ | $0.52^{***}$ |
| Gender [female]*Journal rank [Q2] | | | | $0.39^{***}$ | $0.46^{***}$ | $0.48^{***}$ | $0.47^{***}$ | $0.58^{***}$ |
| Gender [female]*Journal rank [Q3] | | | | 0.91 | 0.94 | 0.87 | 0.84 | 0.88 |
| Gender [female]*Journal rank [Q4] | | | | $0.49^{***}$ | $0.54^{***}$ | $0.49^{***}$ | $0.48^{***}$ | $0.86^{***}$ |
| | | | | | | | | |
| Academic age [2] | | | | | $0.63^{***}$ | $0.67^{***}$ | $0.67^{***}$ | $0.62^{***}$ |
| Academic age [3] | | | | | $0.36^{***}$ | $0.39^{***}$ | $0.39^{***}$ | $0.38^{***}$ |
| Gender [female]*Academic age [2] | | | | | $1.29^{***}$ | $1.25^{***}$ | $1.25^{***}$ | $1.18^{**}$ |
| Gender [female]*Academic age [3] | | | | | $1.23^{**}$ | 1.09 | 1.09 | 1.08 |
| | | | | | | | | |
| Author counts | | | | | | $0.84^{**}$ | $0.85^{***}$ | $0.69^{***}$ |
| Gender [female]*Author count | | | | | | $0.93^{***}$ | $0.95^{**}$ | $0.88^{***}$ |
| | | | | | | | | |
| Country-level collaboration [Y] | | | | | | | $0.80^{***}$ | 1.13 |
| Institution-level collaboration [Y] | | | | | | | 0.97 | $0.86^{***}$ |
| Gender [female]*Country-level collaboration [Y] | | | | | | | $0.54^{***}$ | $0.49^{***}$ |
| Gender [female]*Institution-level collaboration [Y] | | | | | | | $0.87^{**}$ | $0.851^{**}$ |
| **Random effects** | | | | | | | | |
| Dispersion parameter | | | | | | | | 0.36 |
| $\tau_{00}$ | | | | | | | | $0.40_{country}$ |
| $\tau_{11}$ | | | | | | | | $0.18_{country.Gender[female]}$ |
| $\rho_{01}$ | | | | | | | | $0.53_{country}$ |
| N | | | | | | | | 197 |
| Observations | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 566,022 |
| Marginal $R^2$/ Conditional $R^2$ | 0.04 / NA | 0.07 / NA | 0.10 / NA | 0.21 / NA | 0.21 / NA | 0.21 / NA | 0.21 / NA | 0.21 / 0.12 |
| AIC | 1,289,639 | 1,258,360 | 1,251,208 | 1,212,349 | 1,210,242 | 1,209,874 | 1,209,447 | 1,173,564 |

Significance level: < 0.01 ‘***’; <0.05 ‘**’ ; <0.01 ‘*’ .

Table 3: Regression results of the Incidence Rate Ratios (IRR) of Twitter mention counts. Control variables are gradually added from Model 0 with only gender to Model 6. Model 7 considers the random effects of countries of affiliation of authors based on Model 6.

| | **Results of model comparison** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Model 0** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** | **Model 7** |
| ***Predictors*** | ***IRR*** | ***IRR*** | ***IRR*** | ***IRR*** | ***IRR*** | ***IRR*** | ***IRR*** | ***IRR*** |
| Intercept | $0.96^{***}$ | $2.79^{***}$ | $1.91^{***}$ | $1.92^{***}$ | $2.04^{***}$ | $2.09^{***}$ | $2.02^{***}$ | $2.79^{***}$ |
| Gender [female] | $1.20^{***}$ | 1.22 | 1.30 | 1.13 | 1.12 | 1.08 | 1.13 | 1.22 |
| Discipline [Agri] | | $0.31^{***}$ | $0.33^{***}$ | $0.41^{***}$ | $0.40^{***}$ | $0.39^{***}$ | $0.39^{***}$ | $0.31^{***}$ |
| Discipline [Eng & Tech] | | $0.19^{***}$ | $0.19^{***}$ | $0.21^{***}$ | $0.20^{***}$ | $0.20^{***}$ | $0.20^{***}$ | $0.19^{***}$ |
| Discipline [Hum] | | $0.25^{***}$ | $0.24^{***}$ | $0.26^{***}$ | $0.26^{***}$ | $0.26^{***}$ | $0.26^{***}$ | $0.19^{***}$ |
| Discipline [Med & Hea] | | $0.53^{***}$ | $0.52^{***}$ | $0.63^{***}$ | $0.61^{***}$ | $0.59^{***}$ | $0.59^{***}$ | $-0.54^{***}$ |
| Discipline [Natur] | | $0.31^{***}$ | $0.32^{***}$ | $0.33^{***}$ | $0.32^{***}$ | $0.32^{***}$ | $0.32^{***}$ | $-0.99^{***}$ |
| Discipline [Soci] | | $0.60^{***}$ | $0.61^{***}$ | 0.66 | $0.66^{***}$ | $0.64^{***}$ | $0.64^{***}$ | $-0.51^{***}$ |
| Gender [female]*Discipline [Agri] | | 0.83 | 0.77 | $0.69^{**}$ | $0.70^{**}$ | 0.72 | $0.71^{**}$ | $-0.33^{**}$ |
| Gender [female]*Discipline [Eng & Tech] | | 0.82 | 0.81 | $0.75^{*}$ | $0.71^{**}$ | $0.75^{*}$ | 0.73 | $-0.26$ |
| Gender [female]*Discipline [Hum] | | 0.85 | 0.84 | 0.80 | 0.78 | 0.78 | 0.77 | $-0.32^{**}$ |
| Gender [female]*Discipline [Med & Hea] | | 0.93 | 0.90 | 0.82 | 0.79 | 0.83 | 0.83 | $-0.28^{*}$ |
| Gender [female]*Discipline [Natur] | | 0.84 | 0.81 | 0.77 | 0.74 | 0.80 | 0.80 | $-0.29^{**}$ |
| Gender [female]*Discipline [Soci] | | $0.67^{**}$ | $0.64^{***}$ | $0.68^{**}$ | $0.66^{***}$ | $0.65^{***}$ | $0.64^{***}$ | $-0.47^{***}$ |
| Cohort [2013] | | | $1.31^{***}$ | $1.28^{***}$ | $1.28^{***}$ | $1.28^{***}$ | $1.27^{***}$ | $0.28^{***}$ |
| Cohort [2014] | | | $1.59^{***}$ | $1.55^{***}$ | $1.53^{***}$ | $1.52^{***}$ | $1.52^{***}$ | $0.46^{***}$ |
| Cohort [2015] | | | $1.59^{***}$ | $1.54^{***}$ | $1.50^{***}$ | $1.49^{***}$ | $1.49^{***}$ | $0.47^{***}$ |
| Cohort [2016] | | | $1.90^{***}$ | $-1.02^{***}$ | $-0.62^{***}$ | $0.62^{***}$ | $0.60^{***}$ | $0.64^{***}$ |
| Gender [female]*Cohort [2013] | | | $0.92^{***}$ | 0.96 | $0.94^{**}$ | $0.92^{***}$ | $0.93^{***}$ | $-0.10^{***}$ |
| Gender [female]*Cohort [2014] | | | $0.87^{***}$ | $0.93^{***}$ | $0.92^{***}$ | $0.89^{***}$ | $0.89^{***}$ | $-0.12^{***}$ |
| Gender [female]*Cohort [2015] | | | $1.09^{***}$ | $1.18^{***}$ | $1.18^{***}$ | $1.15^{***}$ | $1.16^{***}$ | $0.12^{***}$ |
| gender [female]*Cohort [2016] | | | $1.05^{**}$ | $1.13^{***}$ | $1.11^{***}$ | $1.08^{***}$ | $1.10^{***}$ | $0.07^{***}$ |
| Journal rank [Q1] | | | | $1.30^{***}$ | $1.26^{***}$ | $1.28^{***}$ | $1.28^{***}$ | $0.07^{**}$ |
| Journal rank [Q2] | | | | $0.63^{***}$ | $0.61^{***}$ | $0.62^{***}$ | $0.61^{***}$ | $-0.53^{***}$ |
| Journal rank [Q3] | | | | $0.54^{***}$ | $0.52^{***}$ | $0.52^{***}$ | $0.52^{***}$ | $-0.66^{***}$ |
| Journal rank [Q4] | | | | $0.66^{***}$ | $0.63^{***}$ | $0.62^{***}$ | $0.63^{***}$ | $-0.55^{***}$ |
| Gender [female]*Journal rank [Q1] | | | | $1.11^{***}$ | $1.11^{*}$ | $1.13^{**}$ | $1.11^{**}$ | $0.20^{***}$ |
| Gender [female]*Journal rank [Q2] | | | | $1.06^{***}$ | 1.08 | 1.08 | 1.08 | $0.19^{***}$ |
| Gender [female]*Journal rank [Q3] | | | | $1.52^{***}$ | $1.47^{***}$ | $1.35^{***}$ | $1.35^{***}$ | $1.34^{***}$ |
| Gender [female]*Journal rank [Q4] | | | | $0.70^{***}$ | $0.71^{***}$ | $0.64^{***}$ | $0.64^{***}$ | $-0.18^{**}$ |
| Academic age [2] | | | | | $1.04^{***}$ | $1.04^{***}$ | $1.05^{***}$ | $0.11^{***}$ |
| Academic age [3] | | | | | $0.13^{***}$ | $1.14^{***}$ | $1.14^{***}$ | $1.14^{***}$ |
| Gender [female]*Academic age [2] | | | | | $1.18^{***}$ | $1.19^{***}$ | $1.19^{***}$ | $0.13^{***}$ |
| Gender [female]*Academic age [3] | | | | | $1.16^{***}$ | $1.16^{***}$ | $1.16^{***}$ | $0.14^{***}$ |
| Author counts | | | | | | $0.99^{**}$ | $0.98^{***}$ | $0.04^{***}$ |
| Gender [female]*Author count | | | | | | $0.94^{***}$ | $0.95^{***}$ | $-0.05^{***}$ |
| Country-level collaboration [Y] | | | | | | | $1.22^{***}$ | 0.02 |
| Institution-level collaboration [Y] | | | | | | | $1.12^{***}$ | $0.18^{***}$ |
| Gender [female]*Country-level collaboration [Y] | | | | | | | $0.83^{***}$ | $-0.12^{***}$ |
| Gender [female]*Institution-level collaboration [Y] | | | | | | | $0.91^{***}$ | $-0.11^{***}$ |
| **Random effects** | | | | | | | | |
| Dispersion parameter | | | | | | | | 0.36 |
| $\tau_{00}$ | | | | | | | | $0.21_{country}$ |
| $\tau_{11}$ | | | | | | | | $0.06_{country.Gender[female]}$ |
| $\rho_{01}$ | | | | | | | | $-0.37_{country}$ |
| N | | | | | | | | 197 |
| Observations | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 566,022 |
| Marginal $R^2$/ Conditional $R^2$ | 0.04 / NA | 0.07 / NA | 0.10 / NA | 0.21 / NA | 0.21 / NA | 0.21 / NA | 0.21 / NA | 0.21 / 0.12 |
| AIC | 1,289,639 | 1,258,360 | 1,251,208 | 1,212,349 | 1,210,242 | 1,209,874 | 1,209,447 | 1,173,564 |

Significance level: < 0.01 ‘***’; <0.05 ‘**’ ; <0.01 ‘*’ .

Table 4: Logistic regression results of the Odds Ratios (OR) of self-promotion on Twitter. Control variables are gradually added from Model 0 with only gender to Model 7. Model 8 considers the random effects of countries of affiliation of authors based on Model 7.

| | Results of model comparison | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Model 0** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** | **Model 7** | **Model 8** |
| ***Predictors*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** | ***QR*** |
| Intercept | $0.02^{***}$ | $0.02^{***}$ | $0.01^{**}$ | $0.01^{***}$ | $0.01^{***}$ | $0.01^{***}$ | $0.01^{***}$ | $0.01^{***}$ | $0.01^{***}$ |
| Gender [female] | 0.98 | 0.47 | $0.36^{**}$ | $0.34^{**}$ | $0.34^{**}$ | $0.33^{**}$ | $0.33^{**}$ | $0.27^{**}$ | $0.25^{**}$ |
| Discipline [Agri] | | $0.43^{***}$ | $0.45^{***}$ | $0.47^{***}$ | $0.46^{***}$ | $0.46^{***}$ | $0.46^{***}$ | $0.56^{**}$ | $0.47^{**}$ |
| Discipline [Eng & Tech] | | $0.19^{***}$ | $0.19^{***}$ | $0.19^{***}$ | $0.19^{***}$ | $0.17^{***}$ | $0.17^{***}$ | $0.32^{***}$ | $0.31^{***}$ |
| Discipline [Hum] | | $2.09^{***}$ | $2.20^{***}$ | $2.40^{***}$ | $2.42^{***}$ | $1.74^{**}$ | $1,76^{**}$ | $2.22^{***}$ | 1.39 |
| Discipline [Med & Hea] | | 0.97 | 1.02 | 1.05 | 1.01 | 1.07 | 1.07 | 0.96 | 0.71 |
| Discipline [Natur] | | 0.76 | 0.80 | 0.74 | 0.71 | 0.69 | 0.69 | 0.87 | 0.79 |
| Discipline [Soci] | | $2.99^{***}$ | $3.16^{***}$ | $3.32^{***}$ | $3.29^{***}$ | $2.54^{***}$ | $2.55^{***}$ | $2.65^{***}$ | $1.89^{**}$ |
| Gender [female]*Discipline [Agri] | | $2.47^{*}$ | $2.60^{*}$ | $2.56^{*}$ | $2.54^{*}$ | $2.58^{*}$ | $2.59^{*}$ | $3.55^{**}$ | $2.94^{*}$ |
| Gender [female]*Discipline [Eng & Tech] | | 1.75 | 1.79 | 1.85 | 1.84 | 1.90 | 1.89 | 2.43 | 2.46 |
| Gender [female]*Discipline [Hum] | | 1.84 | 1.92 | 1.94 | 1.93 | 1.92 | 1.91 | $2.77^{*}$ | 2.33 |
| Gender [female]*Discipline [Med & Hea] | | 1.90 | 2.01 | 2.02 | 2.01 | 2.01 | 2.01 | $2.91^{*}$ | 2.29 |
| Gender [female]*Discipline [Natur] | | 1.84 | 1.93 | 1.99 | 1.97 | 2.05 | 2.04 | $2.85^{*}$ | 2.54 |
| Gender [female]*Discipline [Soci] | | 1.67 | 1.75 | 1.78 | 1.77 | 1.78 | 1.78 | 2.56 | 2.03 |
| Cohort [2013] | | | $1.45^{***}$ | $1.47^{***}$ | $1.47^{***}$ | $1.48^{***}$ | $1.48^{***}$ | $1.35^{***}$ | $1.39^{***}$ |
| Cohort [2014] | | | $1.70^{***}$ | $1.73^{***}$ | $1.72^{***}$ | $1.76^{***}$ | $1.75^{***}$ | $1.49^{***}$ | $1.61^{***}$ |
| Cohort [2015] | | | $2.08^{***}$ | $2.16^{***}$ | $2.14^{***}$ | $2.21^{***}$ | $2.20^{***}$ | $1.80^{***}$ | $2.02^{***}$ |
| Cohort [2016] | | | $2.33^{***}$ | $2.44^{***}$ | $2.41^{***}$ | $2.52^{***}$ | $2.51^{***}$ | $1.95^{***}$ | $2.24^{***}$ |
| Gender [female]*Cohort [2013] | | | 1.07 | 1.07 | 1.07 | 1.06 | 1.07 | 1.12 | 1.11 |
| Gender [female]*Cohort [2014] | | | $1.25^{***}$ | $1.26^{***}$ | $1.26^{***}$ | $1.25^{***}$ | $1.26^{***}$ | $1.34^{***}$ | $1.33^{**}$ |
| Gender [female]*Cohort [2015] | | | $1.30^{***}$ | $1.30^{***}$ | $1.30^{***}$ | $1.29^{***}$ | $1.30^{***}$ | $1.36^{**}$ | $1.36^{**}$ |
| gender [female]*Cohort [2016] | | | $1.44^{***}$ | $1.44^{***}$ | $1.44^{***}$ | $1.43^{***}$ | $1.43^{***}$ | $1.55^{***}$ | $1.55^{**}$ |
| Journal rank [Q1] | | | | $1.42^{***}$ | $1.40^{***}$ | $1.50^{***}$ | $1.50^{***}$ | $1.22^{**}$ | 1.17 |
| Journal rank [Q2] | | | | $0.71^{***}$ | $0.70^{***}$ | $0.70^{***}$ | $0.72^{***}$ | 0.78 | $0.84^{**}$ |
| Journal rank [Q3] | | | | $0.42^{***}$ | $0.42^{***}$ | $0.42^{***}$ | $0.42^{***}$ | $0.55^{**}$ | $0.63^{**}$ |
| Journal rank [Q4] | | | | $0.28^{***}$ | $0.28^{***}$ | $0.28^{***}$ | $0.28^{***}$ | $0.42^{***}$ | $0.54^{***}$ |
| Gender [female]*Journal rank [Q1] | | | | 1.02 | 1.02 | 1.04 | 1.03 | 0.97 | 0.90 |
| Gender [female]*Journal rank [Q2] | | | | 1.14 | 1.15 | 1.15 | 1.15 | 1.05 | 1.00 |
| Gender [female]*Journal rank [Q3] | | | | 1.03 | 1.03 | 1.03 | 1.03 | 0.94 | 0.96 |
| Gender [female]*Journal rank [Q4] | | | | 0.73 | 0.73 | 0.73 | 0.72 | $0.65^{*}$ | 0.69 |
| Academic age [2] | | | | | 1.05 | $1.15^{***}$ | $1.15^{***}$ | $1.09^{**}$ | |
| Academic age [3] | | | | | $1.35^{***}$ | $1.51^{***}$ | $1.51^{***}$ | $1.37^{***}$ | |
| Gender [female]*Academic age [2] | | | | | 0.96 | 0.96 | 0.96 | 0.97 | 0.99 |
| Gender [female]*Academic age [3] | | | | | 1.06 | 1.06 | 1.06 | 1.07 | 1.09 |
| Author counts | | | | | | $0.77^{**}$ | $0.76^{***}$ | $0.74^{***}$ | $0.86^{***}$ |
| Gender [female]*Author count | | | | | | 0.98 | 0.98 | 0.99 | 0.98 |
| Country-level collaboration [Y] | | | | | | | $1.29^{***}$ | $1.25^{***}$ | $0.87^{**}$ |
| Institution-level collaboration [Y] | | | | | | | $1.14^{***}$ | $1.10^{**}$ | $1.28^{***}$ |
| Gender [female]*Country-level collaboration [Y] | | | | | | | 1.06 | 1.09 | 1.18 |
| Gender [female]*Institution-level collaboration [Y] | | | | | | | $0.89^{*}$ | 0.90 | $0.88^{*}$ |
| Tweeted by others [Y] | | | | | | | | $3.65^{***}$ | $2.88^{***}$ |
| Counts of others' tweets | | | | | | | | $1.36^{**}$ | $1.31^{***}$ |
| Gender [female]*Tweeted by others [Y] | | | | | | | | $0.75^{***}$ | $0.70^{***}$ |
| Gender [female]*Counts of others' tweets | | | | | | | | 1.03 | $1.04^{**}$ |
| **Random effects** | | | | | | | | | |
| $\tau_{00}$ | | | | | | | | | $0.42_{country}$ |
| $\tau_{11}$ | | | | | | | | | $0.10_{country.Gender[female]}$ |
| $\rho_{01}$ | | | | | | | | | $0.45_{country}$ |
| N | | | | | | | | | 197 |
| Observations | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 567,162 | 566,022 |
| Marginal $R^2$/ Conditional $R^2$ | 0.00 / NA | 0.10 / NA | 0.13 / NA | 0.19 / NA | 0.19 / NA | 0.20 / NA | 0.21 / NA | 0.26 / NA | 0.29 / 0.18 |
| AIC | 89,762 | 86,978 | 86,046 | 84,293 | 84,192 | 83,741 | 83,693 | 78,911 | 74,390 |

Significance level: < 0.01 '***'; <0.05 '**' ; <0.01 '*' .