

1 **The effect of bioRxiv preprints on citations and altmetrics**

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10 **1. Abstract**

11 A potential motivation for scientists to deposit their scientific work as preprints is to enhance
12 its citation or social impact, an effect which has been empirically observed for preprints in
13 physics, astronomy and mathematics deposited to arXiv. In this study we assessed the citation
14 and altmetric advantage of bioRxiv, a preprint server for the biological sciences. We retrieved
15 metadata of all bioRxiv preprints deposited between November 2013 and December 2017,
16 and matched them to articles that were subsequently published in peer-reviewed journals.
17 Citation data from Scopus and altmetric data from Altmetric.com were used to compare
18 citation and online sharing behaviour of bioRxiv preprints, their related journal articles, and
19 non-deposited articles published in the same journals. We found that bioRxiv-deposited
20 journal articles received a sizeable citation and altmetric advantage over non-deposited
21 articles. Regression analysis reveals that this advantage is not explained by multiple
22 explanatory variables related to the article and its authorship. bioRxiv preprints themselves
23 are being directly cited in journal articles, regardless of whether the preprint has been
24 subsequently published in a journal. bioRxiv preprints are also shared widely on Twitter and
25 in blogs, but remain relatively scarce in mainstream media and Wikipedia articles, in
26 comparison to peer-reviewed journal articles.

27 **2. Introduction**

28 Preprints, typically defined as versions of scientific articles that have not yet been formally
29 accepted for publication in a peer-reviewed journal, are an important feature of modern
30 scholarly communication (Berg et al., 2016). Major motivations for the scholarly community
31 to adopt the use of preprints have been proposed as early discovery (manuscripts are available
32 to the scientific community earlier, bypassing the time-consuming peer review process), open
33 access (manuscripts are publicly available without having to pay expensive fees or
34 subscriptions) and early feedback (authors can receive immediate feedback from the scientific
35 community to include in revised versions) (Maggio et al., 2018). An additional incentive for
36 scholars to deposit preprints may be to increase citation counts and/or altmetric indicators
37 such as shares on social media platforms. For example, recent surveys conducted by the
38 Association for Computational Linguistics (ACL) and Special Interest Group on Information
39 Retrieval (SIGIR), which investigated community members behaviours and opinions
40 surrounding preprints, found that 32 and 15 % of respondents were respectively motivated to
41 deposit preprints “to maximize the paper’s citation count” (Foster et al., 2017; Kelly, 2018).

42 A body of evidence has emerged which supports the notion of a citation differential between
43 journal articles that were previously deposited as preprints and those that were not, with
44 several studies concluding that arXiv-deposited articles subsequently received more citations
45 than non-deposited articles in the same journals (Davis and Fromerth, 2007, Moed, 2007;
46 Gentil-Beccot et al., 2010; Larivière et al., 2014). Multiple factors have been proposed as
47 drivers of this citation advantage, including increased readership due to wider accessibility
48 (the “open access effect”), earlier accumulation of citations due to the earlier availability of
49 articles to be read and cited (the “early access effect”), authors preferential deposition of their
50 highest quality articles as preprints (the “self-selection effect”), or a combination thereof
51 (Kurtz et al., 2005). Whilst a citation advantage has been well documented for articles
52 deposited to arXiv, the long-established nature of depositing preprints in physics, astronomy
53 and mathematics may make it unsuitable to extend the conclusions of these studies to other
54 subject-specific preprint repositories, where preprint deposition is a less established practice.

55 bioRxiv is a preprint repository aimed at researchers in the biological sciences, launched in
56 November 2013 and hosted by the Cold Spring Harbor Laboratory (<https://www.biorxiv.org/>).
57 As a relatively new service, it presents an interesting target for analysing impact metrics in a
58 community where preprints have been less widely utilised in comparison to the fields of
59 physics, astronomy and mathematics (Ginsparg, 2016). A recent study by Serghiou and

60 Ioannidis (2018) provided initial insights into the potential citation and altmetric advantage of
61 bioRxiv-deposited articles over non-deposited articles, finding that bioRxiv-deposited articles
62 had significantly higher citation counts and altmetric scores than non-deposited articles.

63 In this study, we investigate citation and altmetric behaviour of bioRxiv preprints and their
64 respective published papers, and compare them to papers not deposited to bioRxiv to
65 determine if a citation and/or altmetric advantage exists. Our study builds on the study of
66 Serghiou and Ioannidis (2018) in several ways: (1) we take into account a longer time period
67 of analysis, from November 2013 to December 2017 (approximately one year longer than that
68 analysed by Serghiou and Ioannidis (2018)), (2) we investigate longitudinal trends in citation
69 behavior for preprints and their published papers, (3) we include a wider range of altmetric
70 indicators including tweets, blogs, mainstream media articles, Wikipedia mentions and
71 Mendeley reads, (4) we conduct regression analysis to investigate the influence of multiple
72 factors related to publication venue and authorship, such as the journal impact factor, or
73 number of co-authors per paper, which may have an effect on citation and altmetric
74 differentials between articles deposited to bioRxiv and those not. Whilst we do not claim
75 *causative* relationships in this study, we aim to shed light on factors that should be considered
76 in discussions centered on preprint citation and altmetric advantages, and put our findings into
77 the context of previous studies conducted on other preprint repositories.

78 **3. Methods**

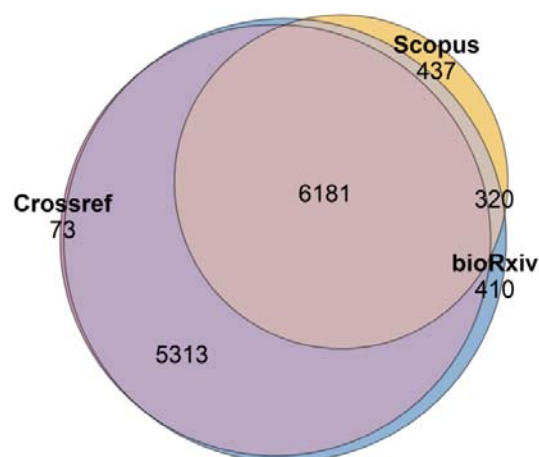
79 *3.1 Preprint and Article Metadata*

80 Basic metadata of all preprints submitted to bioRxiv between November 2013 and December
81 2017 were harvested in April 2019 via the Crossref public Application Programming Interface
82 (API) (N = 18,841), using the *rcrossref* package for R (Chamberlain et al., 2019). Links to
83 articles subsequently published in peer-reviewed journals were discovered via three
84 independent methods:

85 (1) Via the ‘relationship’ property stored on the Crossref preprint metadata record. These
86 links are maintained and routinely updated by bioRxiv through monitoring of databases
87 such as Crossref and PubMed, or through information provided directly by the authors
88 (personal correspondence with bioRxiv representative, October 2018). Each DOI
89 contained in the ‘relationship’ property was queried via the Crossref API to retrieve the
90 metadata record of the published article.

91 (2) Via the publication notices published directly on the bioRxiv website (see, for example,
92 <https://doi.org/10.1101/248278>). bioRxiv web pages were crawled in April 2019 using
93 the *RSelenium* and *rvest* packages for R (Wickham, 2016; Harrison, 2019) and DOIs of
94 published articles were extracted from the relevant HTML node of the publication
95 notices.

96 (3) Via matching of preprints records in Scopus (leveraging the data infrastructure of the
97 German Competence Centre for Bibliometrics:
98 <http://www.forschungsinfo.de/Bibliometrie/en/index.php>). Our matching procedure relied
99 on direct correspondence of the surname and first letter of the given name of the first
100 author, and fuzzy matching of the article title or first 100 characters of the abstract
101 between the bioRxiv preprint and Scopus record. Fuzzy matching was conducted with the
102 R package *stringdist* (van der Loo, 2018), using the Jaro distance algorithm and a
103 similarity measure of 80 %. Matches were further validated by comparison of the author
104 count of the preprint and Scopus record.



105

106 **Figure 1: Proportional Venn diagram showing overlap between preprint-published article links**
107 **discovered via three separate methodologies.** ‘Crossref’ refers to those discovered via the Crossref
108 ‘relationship’ property, ‘bioRxiv’ to those discovered via the bioRxiv website, and ‘Scopus’ to those discovered
109 via fuzzy matching of preprint titles and abstracts to Scopus records.

110 Overlapping links produced by the three separate methodologies (Figure 1) were merged to
111 create a single set of preprint-published article DOI links. In rare cases of disagreement
112 between methodologies (e.g. where the published paper DOI identified via the bioRxiv
113 website differed to that identified via Crossref or our Scopus fuzzy-matching methodology),
114 we prioritised the record from the bioRxiv website, followed by the Crossref record, with our
115 Scopus fuzzy-matching methodology as the lowest priority. We discovered a small number of

116 cases where authors had created separate records for multiple preprint versions rather than
117 uploading a new version on the same record (e.g. <https://doi.org/10.1101/122580> and
118 <https://doi.org/10.1101/125765>). For these cases we selected the earlier posted record and
119 discarded the later record from our dataset, to ensure that only a single non-duplicated
120 published article exists for each preprint. Following these steps we produced a set of 12,767
121 links between deposited preprints and published articles, representing 67.8 % of all preprints
122 deposited over the same time period.

123 *3.2 Citation and altmetric analysis dataset*

124 For the purposes of citation and altmetric analysis, we limited the set of journal articles
125 retrieved in the previous step to those that were published in the 50-month period between
126 November 2013 (coinciding with the launch of bioRxiv) and December 2017. We selected
127 this time period as we use an archived Scopus database ‘snapshot’, which only partially
128 covers articles published in 2018 (thus we only use years with full coverage). We further
129 restricted the set of journal articles to those that could be matched to a record in Scopus via
130 direct, case-insensitive correspondence between DOIs, to ‘journal’ publication types, ‘article’
131 or ‘review’ document types, and to articles with reference counts greater than zero, to reduce
132 the rare incidence of editorial material incorrectly classified in Scopus as ‘article’ type
133 documents.

134 Subsequently we built a control group of non-deposited articles for conducting comparative
135 analysis. The control group was generated as follows: for each individual article within our
136 bioRxiv-deposited group, we sampled a single random, non-deposited article published in the
137 same journal and same calendar month. Articles in the control group were limited to ‘journal’
138 publication types, ‘article’ or ‘review’ document types, and records with reference counts
139 greater than zero. We therefore generated a control group that matches our bioRxiv-deposited
140 group in terms of journals and article ages.

141 A potential weakness of this matching procedure lies in the inclusion of articles published
142 within large multidisciplinary journals (e.g. PLOS One, Scientific Reports), as it would be
143 unwise to match a biology-focused article with an article from another discipline with
144 drastically different publication and citing behaviours. For articles published in
145 multidisciplinary journals, we therefore conducted an additional procedure prior to sampling,
146 in which articles in both the bioRxiv-deposited and control groups were re-classified into
147 Scopus subject categories based on the most frequently cited subject categories amongst their
148 references (modified from the multidisciplinary article classification procedure used in

149 Piwowar et al., 2018). Where categories were cited equally frequently, articles were assigned
150 to multiple categories. For each bioRxiv-deposited article, a single random non-deposited
151 article was sampled from the same journal-month and categories in the control group.

152 Following these steps, we produced an analysis dataset consisting of 7,087 bioRxiv-deposited
153 and 7,087 non-deposited control articles.

154 *3.3 Publication Dates*

155 A methodological consideration when analysing citation data is in the treatment of publication
156 dates. Publication dates for individual articles are reported by multiple outlets (e.g. by
157 Crossref, Scopus and the publishers themselves), but often represent different publication
158 points, such as the date of DOI registration, the Scopus indexing date, or the online and print
159 publication dates reported by the publisher (Haustein et al., 2015). In our study, we implement
160 the Crossref ‘created-date’ property as the canonical date of publication for all articles and
161 citing articles in our datasets, in line with the approach of Fang and Costas (2018). The
162 ‘created-date’ is the date upon which the DOI is first registered and can thus be considered a
163 good proxy for the first online availability of an article at the publisher website. An advantage
164 of this method is that we can report citation counts at a monthly resolution, as advocated by
165 Donner (2018), which may be more suitable than reporting annual citation counts due to the
166 relatively short time-span of our analysis period and rapid growth of bioRxiv. Created-dates
167 of all preprints, articles and citing articles referenced in this study were extracted via the
168 Crossref public API.

169 *3.4 Citation Data*

170 Metadata of citing articles were retrieved from Scopus for all articles in our bioRxiv-
171 deposited and control groups. Citing articles were limited to those published over the time
172 period of our analysis, November 2013 to December 2017. For each published article, we
173 extract all citing articles and retrieve their Crossref created-date, to allow us to aggregate
174 monthly citation counts. A consequence of this approach is that the maximum citation period
175 of an article is variable, limited by the length of time between its publication, and the end of
176 our analysis period in December 2017. For instance, an article published in December 2014
177 would have a maximum citation period of 36 months (from December 2014 to December
178 2017), whilst an article published in June 2017 would have a maximum citation period of 6
179 just months.

180 We additionally extracted records of articles directly citing preprints. Since preprints are not
181 themselves indexed in Scopus, we utilised the Scopus raw reference data, which includes a
182 ‘SOURCETITLE’ field including the location of the cited object. We queried the
183 SOURCETITLE for entries containing the string ‘biorxiv’ (case-insensitive, partial matches),
184 and retrieved a total of 4,826 references together with metadata of their Scopus-indexed citing
185 articles. References were matched to preprints via fuzzy-matching of titles and/or direct
186 matching of DOIs, although DOIs were only provided in a minority of cases. In total 4,387
187 references (90.9 %) could be matched to a bioRxiv preprint.

188 *3.5 Altmetrics Data*

189 Altmetric data, including tweets, blogs, mainstream media articles, Wikipedia, and Mendeley
190 reads were retrieved for all deposited and non-deposited articles, as well as for preprints
191 themselves, by querying their DOIs against the Altmetric.com API
192 (<https://api.altmetric.com/>). Where no altmetric information was found for each indicator,
193 counts were recorded as zero. Coverage amongst altmetric indicators was highest for
194 Mendeley reads and Tweets, with 92 % and 91 % of published articles in our dataset receiving
195 at least a single Mendeley read or Tweet. Coverage of Wikipedia mentions was lowest, with
196 only 4 % of our articles being mentioned in Wikipedia.

197 *3.6 Regression analysis*

198 To investigate the influence of additional factors on a citation or altmetric differential between
199 bioRxiv-deposited and non-deposited papers, we conducted regression analysis on citation
200 and altmetric count data with a set of explanatory variables related to the article and its
201 authorship. These variables include the journal impact factor (IF), article open access (OA)
202 status, article type, first and last author country, first and last author academic age, and first
203 and last author gender.

204 IF was calculated independently from Scopus citation data, following the formula:

$$IF_{year} = \frac{Citations_{year-1} + Citations_{year-2}}{Items_{year-1} + Items_{year-2}}$$

205 Note that items were limited to article and review document types, i.e. not including editorial
206 material. Calculating IF independently ensures greater coverage of journals within our dataset
207 compared to using the more commonly-known Journal Citation Reports produced by

208 Clarivate Analytics. A manual comparison between the two datasets, however, suggests good
209 agreement between the two methodologies.

210 Article OA status was determined by querying article DOIs against the Unpaywall API
211 (<https://unpaywall.org>). Unpaywall is a service which locates openly available versions of
212 scientific articles, via harvesting of data from journals and OA repositories. They provide a
213 free API which can be queried via a DOI, returning a response containing information relating
214 to the OA status, license and location of the OA article. We use the Boolean ‘*is_oa*’ resource
215 returned by the Unpaywall API, which classifies articles as OA when the published article is
216 openly available in any form, either on the publishers’ website or via an alternative repository
217 (i.e. we do not distinguish between the ‘Gold’, ‘Green’ and ‘Hybrid’ routes of OA).

218 The country of the first and last author of each article was extracted from Scopus based upon
219 the country in which the authors’ institution/s is/are based. For regression analysis, we
220 classified authors into two categories: those having a US-based affiliation, and those not,
221 following similar approaches employed by Gargouri et al. (2010) and Davis et al. (2008).
222 Such an approach may not capture all of the fine-grain relationships between author countries
223 and citations/altmetrics, however, it is notable that bioRxiv-deposited articles are generally
224 over-represented by US-based authors: approximately 49 % of first and last authors of
225 bioRxiv-deposited articles in our dataset had a US-based affiliation, whilst only around 38 %
226 of first and last authors of non-deposited articles had a US-based affiliation.

227 The academic age of the first and last author of an article, used as a proxy for academic
228 seniority, was determined from the difference between the publication year of the paper in
229 question, and the year of the authors’ first recorded publication in Scopus. Whilst there are
230 limitations to this approach, for example we may not detect authors who publish preferentially
231 in edited volumes not indexed in Scopus, the year of first publication has been found to be a
232 good predictor for both the academic and biological age of a researcher in multiple subject
233 areas (Nane, Larivière and Costas, 2017). To obtain the year of the first recorded publication,
234 we retrieved authors’ publication histories using the Scopus author ID, an identifier assigned
235 automatically by Scopus to associate authors with their publication *oeuvres*. The author ID
236 aims to disambiguate authors based upon affiliations, publication histories, subject areas and
237 co-authorships (Moed et al., 2013). The algorithm aims at higher precision than recall; that is
238 to say, articles grouped under the same author ID are likely to belong to a single author, but
239 the articles of an author may be split between multiple author IDs.

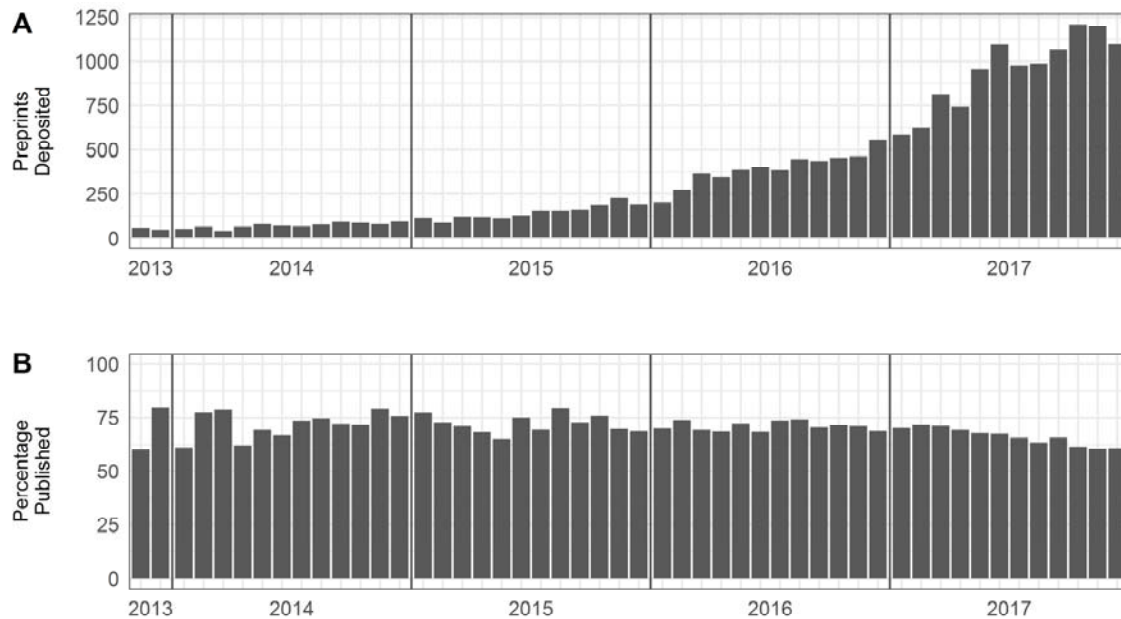
240 Author gender was inferred using the web service Gender API (<https://gender-api.com>).
241 Author first names were extracted from Scopus and stripped of any leading or trailing initials
242 (e.g. “Andrea B.” would become “Andrea”). Gender API predicts gender using a database of
243 >2 million name-gender relationships retrieved from governmental records and data crawled
244 from social networks (Santamaria and Mihaljevic, 2018). The service accepts parameters for
245 localization, which we included from our previously defined dataset of author countries.
246 Gender assignments are returned as “male”, “female”, or “unknown”. Where localized queries
247 returned “unknown”, we repeated the query without the country parameter. For our data, we
248 were able to assign genders to 94.4 % of first authors, and 94.8 % of last authors.

249 Regression analysis was conducted for citation counts (for 6-month, 12-month, and 24-month
250 citation windows) and altmetric counts (for tweets, blogs, mainstream media articles,
251 Wikipedia mentions, and Mendeley reads) using a negative binomial regression model, with
252 the full set of explanatory variables as described above. A negative binomial regression model
253 is more suitable for over-dispersed count data (as is the case with citation and altmetric count
254 data) than a linear regression model (Ajiferuke and Famoye, 2015). Regression was
255 conducted using the R package *MASS* (Venables and Ripley, 2002).

256 **4. Results and Discussion**

257 *4.1 bioRxiv submissions and publication outcomes*

258 Depositions of preprints to bioRxiv grew exponentially between November 2013 and
259 December 2017 (Figure 2). Of the 18,841 preprints posted between 2013 and 2017, our
260 matching methodology identified 12,767 preprints (67.7 %) that were subsequently published
261 in peer reviewed journals. This is a slightly higher rate than the 64.0 % reported by Abdill and
262 Blekhman (2019), which may be due to our analysis occurring later (thus allowing more time
263 for preprints to be published), as well as our more expansive matching methodology which
264 did not rely solely on publication notices on the bioRxiv websites. These results from bioRxiv
265 are broadly similar to those of Larivière et al. (2014) in the context of ArXiv, who found that
266 73 % of ArXiv preprints were subsequently published in peer-reviewed journals, with the
267 proportion decaying in more recent years as a result of the delay between posting preprints
268 and publication in a journal. The stability of the proportion of bioRxiv preprints that
269 proceeded to journal publication between 2013 and 2016 additionally suggests that the rapid
270 increase in the number of preprint submissions was not accompanied by any major decrease
271 in the quality (or at least, the ‘publishability’) of preprints over this time period.



272

273 **Figure 2: Development of bioRxiv submissions and publication outcomes over time. (A)** Submissions of
274 preprints to bioRxiv. **(B)** Percentage of bioRxiv preprints subsequently published in peer-reviewed journals.

275 The median delay time between submission of a preprint and publication was found to be 154
276 days, in comparison to the 166 days reported by Abdill and Blekhman (2019) – the difference
277 can likely be explained by the different points of publication used – whilst we used only the
278 Crossref ‘created-date’, Abdill and Blekhman (2019) prioritised the ‘published-online’ date,
279 and the ‘published-print’ date when ‘published-online’ was not available, only using the
280 ‘created-date’ as a final option. It should be noted that neither of these calculated delay times
281 is representative of the average *review* time of a manuscript submitted to a journal, as authors
282 may not submit their manuscript to a journal immediately on deposition of a preprint, and
283 manuscripts may be subject to several rounds of rejection and resubmission before
284 publication. Nonetheless, the delay time calculated by both our approach and that of Abdill
285 and Blekhman (2019) reveals that preprints effectively shorten the time to public
286 dissemination of an article by 5-6 months compared to the traditional journal publication
287 route.

288 4.2 Citations Analysis

289 4.2.1 bioRxiv citation advantage

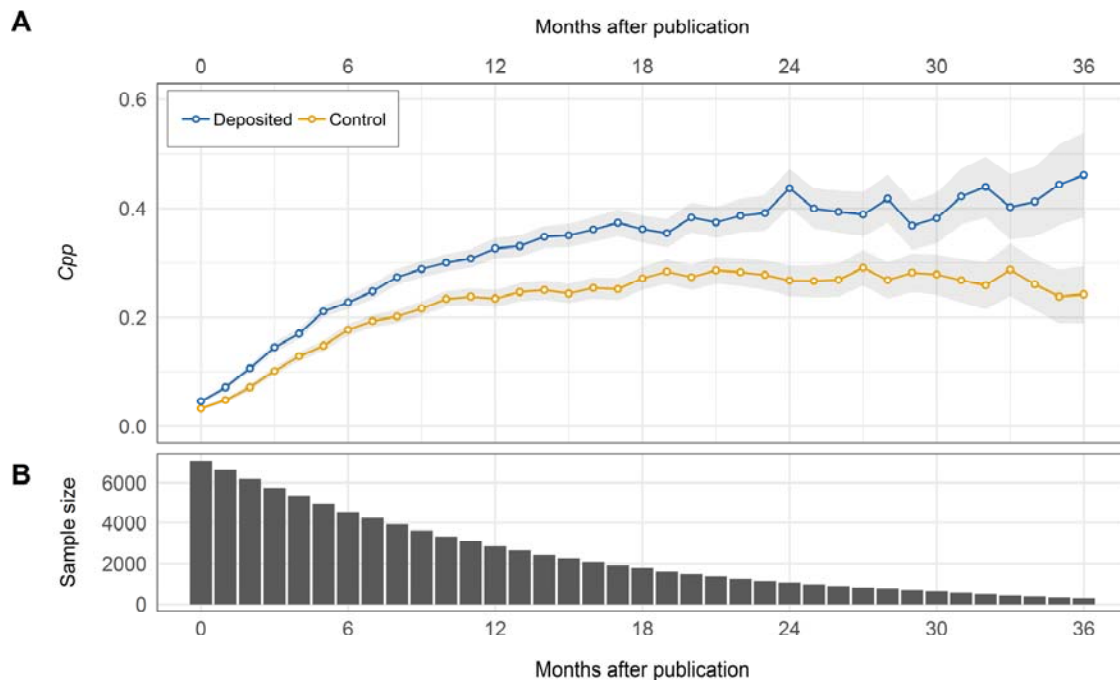
290 For the time period November 2013 to December 2017, we retrieved a total of 47,169
291 citations to journal articles that were previously deposited to bioRxiv, versus 29,298 citations

292 to articles in our non-deposited control group. These numbers give a crude citation advantage
293 of bioRxiv-deposited articles of 61.0 % over non-deposited articles published in the same
294 journal and month. A similar crude citation advantage of bioRxiv-deposited articles was also
295 reported by Serghiou and Ioannidis (2018), despite the usage of different citation data sources
296 - in our study we use citation data derived from Scopus whilst Serghiou and Ioannidis (2018)
297 use citation data derived from Crossref. A recent analysis has found similar overall coverage
298 of publications and citations of both Scopus and Crossref (Harzing, 2019), however there are
299 still some major gaps in Crossref citation coverage due to non-support of certain Crossref
300 members of the Open Citations Initiative (<https://i4oc.org>), most notably Elsevier, which may
301 still introduce systematic bias into large-scale citation analyses.

302 To explore how the bioRxiv citation advantage develops over time following publication, we
303 compared average monthly citations per paper (C_{pp}) for each group for the 36 months
304 following journal publication (Figure 3). Citation counts were aggregated at a monthly level
305 for each article, and then counts were log-transformed to normalize the data and reduce the
306 influence of papers with high citation counts (following Thelwall (2016) and Ruocco et al.
307 (2017)). C_{pp} was calculated by taking the mean of the log-transformed citation counts of all
308 articles within a group:

$$C_{pp} = \frac{1}{n} \sum_{i=1}^n \log(\text{Citations}_i + 1)$$

309 We limited our citation window to 36 months due to the small number of articles that were
310 published sufficiently early in our analysis to allow longer citation windows. In general terms,
311 we observe an acceleration of the citation rates of both groups within the first 18 months
312 following publications, and an approximate plateau in citation rates between 18 and 36
313 months. However, the results demonstrate a clear divergence between the two groups
314 beginning directly at the point of publication; at 6 months post-publication the C_{pp} of
315 bioRxiv-deposited articles is 29 % higher than the non-deposited articles, with the monthly
316 advantage growing to 40 % by 12 months post-publication. Between 18-36 months, the
317 citation differential stabilises, with the C_{pp} of the bioRxiv-deposited group remaining ~50 %
318 higher than the control group.



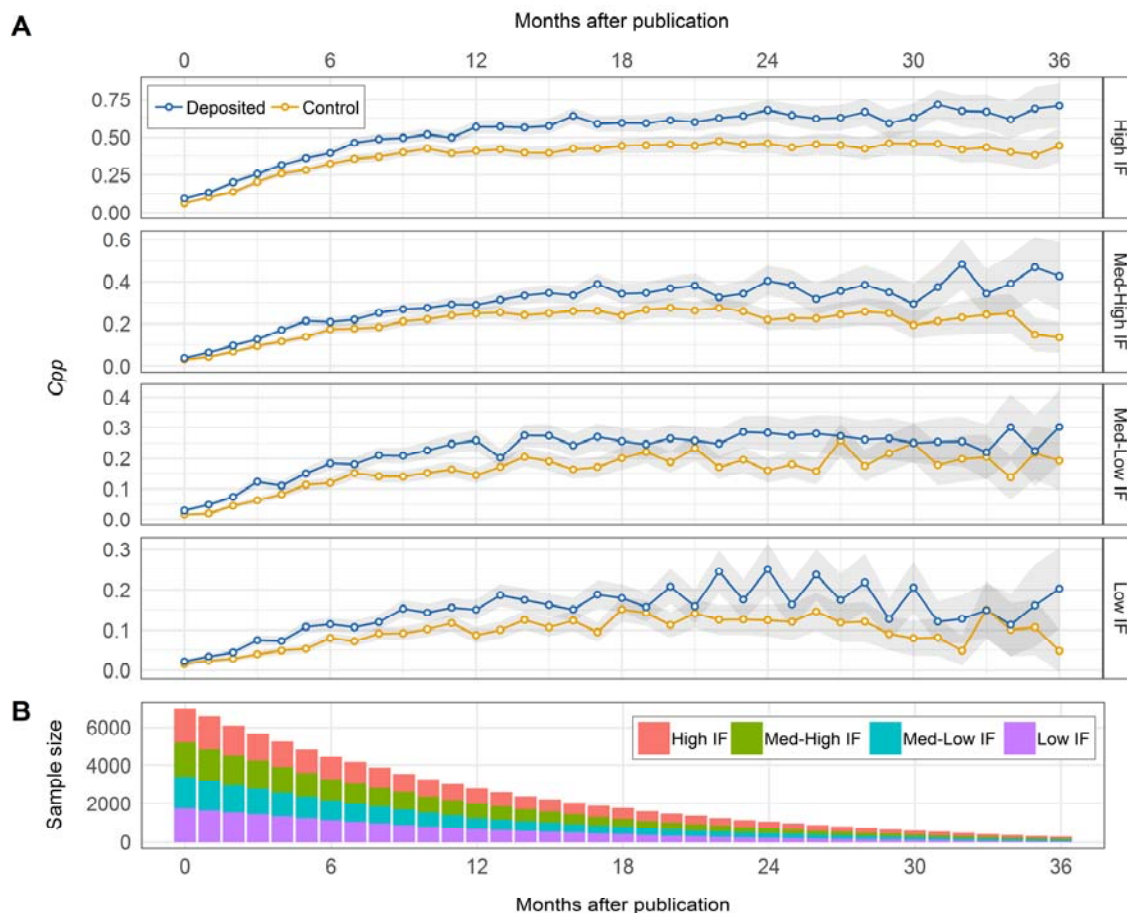
319

320 **Figure 3: Monthly citation rates of bioRxiv-deposited and non-deposited control articles.** (A) Calculated
321 C_{pp} of bioRxiv-deposited articles (blue line) and non-deposited control articles (yellow line) as a function of
322 months following publication. Grey shading represents 95 % confidence intervals. (B) Sample size of each group
323 at each respective time interval. Sample sizes are equal for both groups.

324 The stability of the citation differential between bioRxiv-deposited and non-deposited articles
325 after 18 months means that we cannot attribute the citation advantage solely to an *early access*
326 effect, where articles with preprints receive a short-term acceleration in citations due to their
327 earlier availability and thus longer period to be read and cited. If this were the case we would
328 expect citation rates of both groups to converge after a period of time, as was reported by
329 Moed (2007) in the context of preprints deposited to ArXiv's Condensed Matter section. In
330 the Moed (2007) study, monthly average citation rates of ArXiv-deposited and non-deposited
331 articles converged after approximately 24 months, whilst our data show no sign of similar
332 behaviour. Conversely, other studies tracking longitudinal changes in citation rates of articles
333 deposited in other arXiv communities have found less support for an early access effect
334 (Henneken et al., 2006; Gentil Beccot et al., 2009), with citations for deposited articles
335 remaining higher than non-deposited articles for >5 years following publication.

336 An alternative explanation for the citation advantage of bioRxiv-deposited articles is that of a
337 *quality* effect, which can be manifested either as a quality bias driven by users self-selecting
338 their highest quality articles to deposit (Kurtz et al., 2005; Davis and Fromerth, 2007), or as a
339 quality advantage where high quality articles which are more likely to be selectively cited

340 anyway are made more accessible, thus further boosting their citedness (Gargouri et al.,
 341 2010).



342

343 **Figure 4: Monthly citation rates of bioRxiv-deposited and non-deposited control articles grouped by IF**
 344 **quartiles.** High IF articles are classified as those in a journal with an IF >7.08, Med-High IF between 7.08-4.53,
 345 Med-Low IF between 4.53-3.33, and low IF <3.33. (A) Calculated *Cpp* of bioRxiv-deposited articles (blue line)
 346 and non-deposited control articles (yellow line) as a function of months following publication for High IF (upper
 347 panel), Med-High IF (second top panel), Med-Low IF (third top panel), and Low UF (lower panel) journals.
 348 Grey shading represents 95 % confidence intervals. (B) Sample size of each group at each respective time
 349 interval. Sample sizes and IF distributions are equal for the bioRxiv-deposited and control groups.

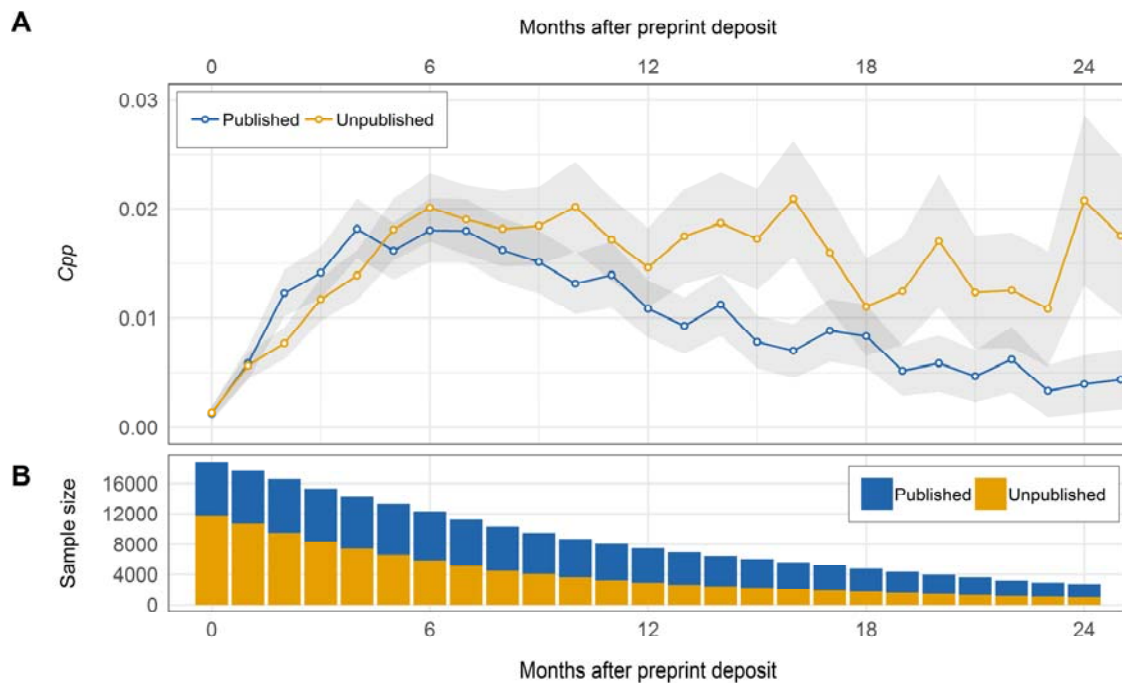
350 We test for a quality advantage through a secondary analysis in which articles were divided
 351 into categories on the basis of their respective journal impact factors (IF). Whilst it is well
 352 recognised that the IF is not a good measure of the quality of an individual article (Cagan,
 353 2013), it remains an important predictor of academic job success in biomedicine (van Dijk,
 354 Manor, Carey; 2014), and can thus be considered as a proxy for researchers' *perception* of the
 355 highest quality outlets to submit their work, i.e. an author is more likely to submit their
 356 perceived higher quality work to a high-IF journal. Each article was assigned an IF on the
 357 basis of its journal and year of publication, and then articles divided into quartiles on the basis

358 of the IF of the journal in which it was published. The upper quartile ('High IF') contained
359 articles in journals with IFs above 7.08, the second highest quartile ("Med-High IF") between
360 7.08 and 4.53, the second lowest quartile ("Med-Low IF") between 4.53 and 3.33, and the
361 lower quartile ("Low IF") lower than 3.33. Monthly citation rates were calculated as
362 previously, within each IF quartile (Figure 4). We observe that the *absolute* citation advantage
363 grows faster in the High IF group, but the *relative* advantage remains remarkably consistent
364 between all four groups, particularly during the first 18 months following publication. If the
365 citation advantage was driven primarily by the articles perceived as researchers highest
366 quality articles, we would expect to see a citation advantage manifested primarily amongst
367 articles in high IF journals, with relatively equal citation rates between bioRxiv-deposited and
368 non-deposited articles in low IF journals. Our data, however, do not appear to support this
369 view.

370 4.2.2 Citations to preprints

371 In addition to retrieving citations to journal articles, we also retrieved details of 4,387
372 citations made directly to preprints themselves. Of these, 2,107 citations were made to
373 preprints that were subsequently published as journal articles, whilst the remaining 2,280
374 citations were made to preprints that remain unpublished. Figure 5 shows a comparison
375 between the *Cpp* of preprints that have subsequently been published in journals, and those that
376 remain unpublished, for a 24 month citation window following deposition of the preprint.
377 Citations to preprints that have been published increase sharply in the first 6 months following
378 deposition, and thereafter decrease, likely a result of other authors preferentially citing the
379 journal version of an article over the preprint. Similar findings have been reported for ArXiv
380 preprints (Brown, 2001; Henneken, 2007; Larivière, 2014). It is interesting to note that in the
381 early months following deposition, unpublished preprints are not cited any less than their
382 published counterparts, and continued to accrue citations many months after deposition, even
383 in the absence of an accompanying journal article. Citing of unpublished preprints is in itself a
384 relatively new development in biological sciences; the National Institutes of Health (NIH), for
385 example, only adopted a policy allowing scientists to cite preprints in grant applications in
386 March 2017 (<https://grants.nih.gov/grants/guide/notice-files/NOT-OD-17-050.html>), and
387 some journals have only recently allowed authors to cite preprints directly in their reference
388 lists (see, e.g. Stoddard and Fox (2019)). Although the number of citations to bioRxiv
389 preprints is still dwarfed by those to journal articles (the *Cpp* of preprints is more than an
390 order of magnitude less than the *Cpp* of the respective publisher papers), the growing

391 willingness of authors to cite unreviewed preprints may factor into ongoing debates
392 surrounding the role of peer review and maintaining the integrity of scientific reporting.

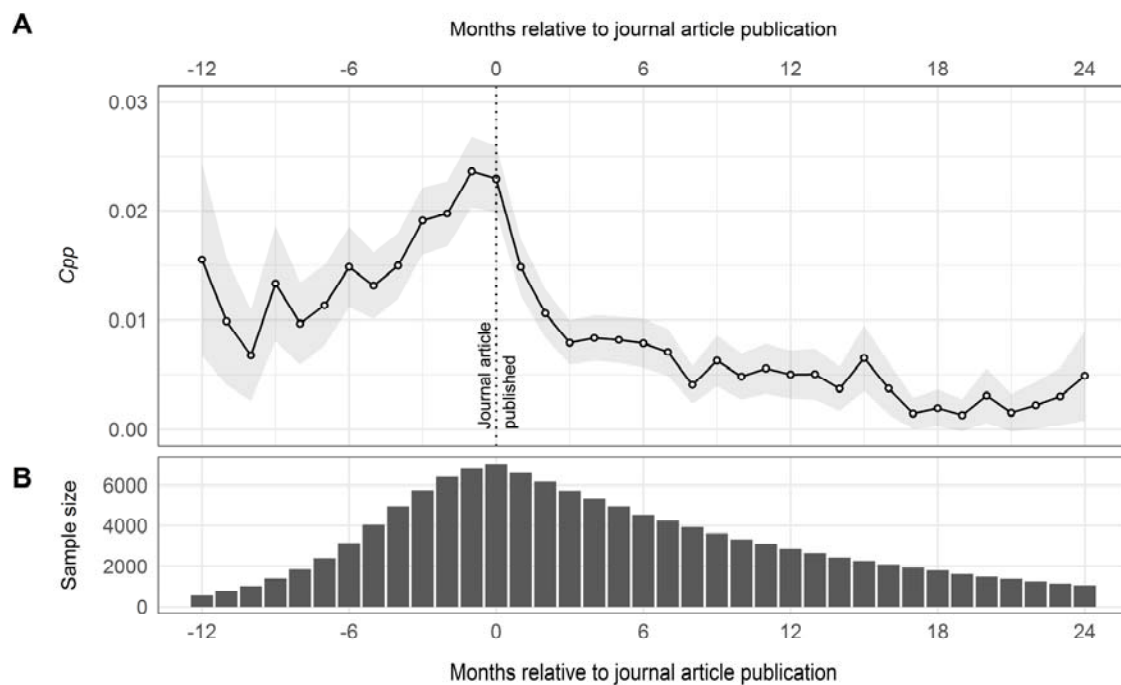


393

394 **Figure 5: Monthly citation rates of bioRxiv preprints.** Preprints are divided into two categories: those which
395 have subsequently been published in peer-reviewed journals, and those which remain unpublished. **(A)**
396 Calculated C_{pp} of published (blue line) and unpublished (yellow line) bioRxiv preprints as a function of months
397 following preprint deposition. Grey shading represents 95 % confidence intervals. **(B)** Sample sizes at each
398 respective time interval.

399 Figure 6 shows the distribution of monthly citation rates to preprints as a function of time
400 before and after the publication of the journal article, i.e. negative citation months indicate the
401 preprint was cited before the journal article was published, and vice versa. Citations appear to
402 become more frequent in the months shortly preceding publication of the journal article, and
403 fall sharply thereafter. A small number of preprints continue to accrue citations more than two
404 years after publication of the journal article, although the origin of these citations is not clear:
405 they may be citations from authors who do not have access to journal publications requiring
406 subscriptions, from authors who remain unaware that a preprint has been published elsewhere
407 or authors failing to update their reference management software with the record from the
408 journal article. A similar analysis of citation aging characteristics of arXiv preprints found
409 that citations to preprints decay rapidly following publication of the journal article (Larivière
410 et al., 2014), whilst reads of arXiv preprints through the NASA Astrophysics Data System

411 also dropped to close to zero following publication of the peer-reviewed article, attributed to
412 authors preferring to read the journal article over the preprint (Henneken et al., 2007).



413

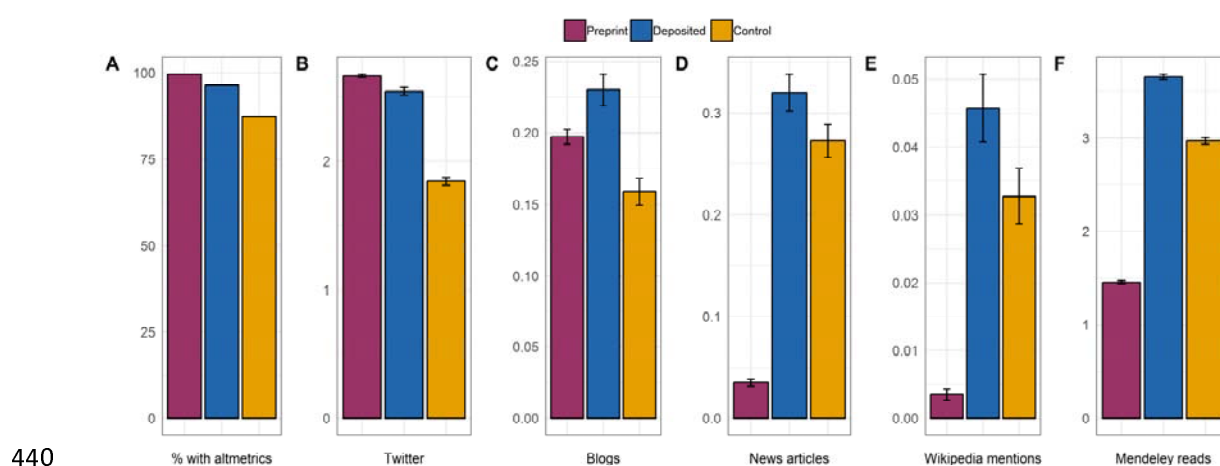
414 **Figure 6: Monthly citation rates of preprints before and after journal publication.** (A) Calculated C_{pp} of
415 bioRxiv preprints for the 12 months prior to, and 24 months following journal publication. Grey shading
416 represents 95 % confidence interval. (B) Sample size of preprints at each time interval.

417 4.3 Altmetrics

418 Altmetric data were retrieved from Altmetric.com and aggregated for all bioRxiv-preprints,
419 bioRxiv-deposited articles and non-deposited control articles (Figure 7). Since altmetrics
420 accrue rapidly in comparison to citations (Bornmann, 2014), we do not aggregate altmetrics
421 into time windows as is more common with citation analysis. Coverage of altmetrics (i.e. the
422 proportion of articles that received at least one count in the various altmetric sources) for
423 bioRxiv-preprints, bioRxiv-deposited articles and non-deposited control articles were 99.7,
424 96.3 and 87.4 %, respectively. It should be noted that the high coverage of altmetrics in
425 bioRxiv-preprints is in large part due to the automatic tweeting of newly published bioRxiv-
426 preprints by the official bioRxiv twitter account (<https://twitter.com/biorxivpreprint>), although
427 we cannot discount automatic tweeting by publishers, journals or individuals for the other
428 categories.

429 Figure 7B-F show mean (log-transformed) counts of tweets, blogs, mainstream media articles,
430 Wikipedia mentions and Mendeley reads, for bioRxiv-preprints, bioRxiv-deposited articles

431 and non-deposited control articles. For all of these data sources, mean counts were higher for
432 the bioRxiv-deposited articles than the non-deposited control articles, indicating that articles
433 that have previously been shared as a preprint are subsequently shared more in various online
434 platforms, in agreement with the previous results of Serghiou and Ioannidis (2018). Mean
435 counts of tweets and blog mentions were broadly similar in bioRxiv-preprints and bioRxiv-
436 deposited articles, but strikingly lower in mainstream news articles and mentions in
437 Wikipedia. This may suggest that whilst bioRxiv preprints are widely shared in ‘informal’
438 social networks by colleagues and peers, they are currently less accepted in ‘formal’ public
439 outlets where peer-reviewed articles remain the preferred source.

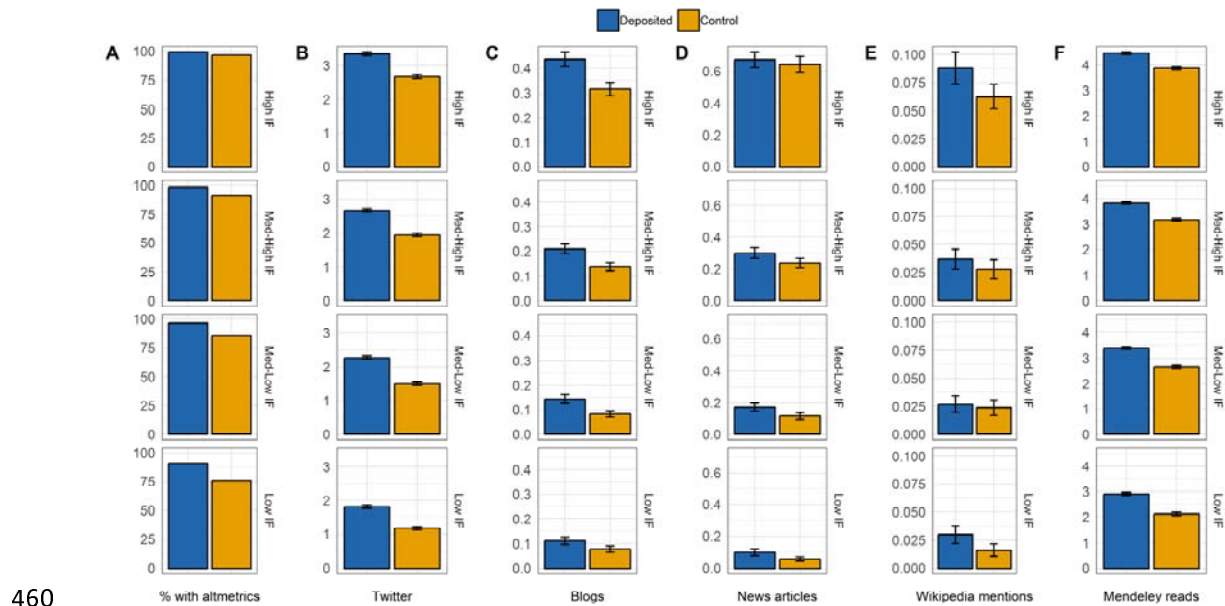


440

441 **Figure 7: Altmetric coverage and counts of bioRxiv-preprints, bioRxiv-deposited articles and non-**
442 **deposited control articles.** Altmetric counts were log-transformed prior to reporting. (A) Percentage of articles
443 associated with any altmetric event covered by Altmetric.com. (B) Mean count of tweets. (C) Mean count of
444 blog mentions. (D) Mean count of mentions in mainstream media articles. (E) Mean count of Wikipedia
445 mentions. (F) Mean count of Mendeley reads.

446 In a similar vein to our previous citation analysis, we conducted a secondary analysis for
447 altmetrics by dividing articles into quartiles on the basis of their journal IF, and comparing
448 altmetric coverage and counts for bioRxiv-deposited and non-deposited control articles
449 (Figure 8). In all cases, altmetric coverage and mean altmetric counts remain higher for the
450 bioRxiv-deposited articles, indicating a preference for sharing of articles previously deposited
451 as preprints over those not deposited. Notable differences are observed between the IF
452 categories, where High IF articles receive more altmetric attention in general than Low IF
453 articles. A similar positive correlation between preprint downloads and IF was reported by
454 Abdill and Blekhman (2019), although in the absence of a ubiquitous source of download data
455 for journal articles, we cannot extend these findings to compare downloads between bioRxiv-
456 deposited and non-deposited articles. As with our citation analysis, the *absolute* differences in

457 altmetric counts between the bioRxiv-deposited and non-deposited articles vary greatly
458 between IF categories, but the *relative* differences remain relatively similar, indicating that
459 there is also no general quality effect driving the bioRxiv altmetric advantage.



460

461 **Figure 8: Altmetric coverage and counts of bioRxiv-deposited articles and non-deposited control articles**
462 **grouped by IF quartiles.** High IF articles are classified as those in a journal with an IF >7.08, Med-High IF
463 between 7.08-4.53, Med-Low IF between 4.53-3.33, and low IF <3.33. Upper panels show results for High IF
464 articles, second top panel for Med-High IF articles, third top panel for Med-Low IF articles, and the lower panel
465 for Low IF articles. Altmetric counts were log-transformed prior to reporting. (A) Percentage of articles
466 associated with any altmetric event covered by Altmetric.com. (B) Mean count of tweets. (C) Mean count of
467 blog mentions. (D) Mean count of mentions in mainstream media articles. (E) Mean count of Wikipedia
468 mentions. (F) Mean count of Mendeley reads.

469 4.4 Regression analysis

470 Results in the previous sections suggest a sizeable citation and altmetric advantage of
471 depositing preprints to bioRxiv, in the absence of consideration of other factors related to
472 publication venue and authorship. In a second step we therefore conducted regression analysis
473 to determine the effect of bioRxiv deposition on citations and altmetrics when controlling for
474 multiple explanatory variables (summarised in Table 1). These explanatory variables are not
475 exhaustive, as citations and altmetrics can be influenced by a number of additional variables
476 which we do not account for (Tahamtan et al., 2016; Didegah et al., 2018), and do not take
477 into account certain *immeasurable* characteristics of an article such as its underlying quality
478 or the quality of the authors themselves. Thus, we refrain from claiming a definitive causative
479 relationship between bioRxiv deposition and a citation or altmetric advantage. However, these

480 variables may help to shed some light on factors which influence citation or altmetric
481 differentials, which may be considered and explored in future studies.

482 **Table 1: Summary statistics for set of 10 explanatory variables included in our regression analysis**

Characteristic	Variable	bioRxiv-deposited (N = 7,087)	Control (N = 7,087)
Journal Impact Factor	Median Journal Impact Factor	4.53	4.53
OA article	% papers that are OA	88.1	83.5
Review article	% review articles	2.79	5.32
Author count	Median author count per article	5	6
First author from USA	% US first authors	49.3	37.4
Last author from USA	% US last authors	49.5	37.6
First author academic age	Median first author academic age (years)	5	5
Last author academic age	Median last author academic age (years)	17	19
First author gender	% articles with female first authors	29.9	36.0
Last author gender	% articles with female last authors	18.0	23.9

483

484 Summary statistics for explanatory variables (Table 1) reveal some key differences between
485 articles that were deposited to bioRxiv, and those that were not. Articles deposited to bioRxiv
486 are more likely to subsequently be published under an OA license than non-deposited article.
487 Here we used the most inclusive categorisation of OA provided by Unpaywall, and did not
488 distinguish between types of OA such as Gold and Green OA. However, given that our two
489 samples are matched with respect to journals, differences arising in OA coverage must result
490 from author choices to make their paper open through Hybrid OA options in subscription
491 journals, or through Green OA self-archiving (e.g. in institutional repositories).

492 We found that 2.8 % of bioRxiv-deposited articles were classified as ‘review’ type
493 documents, despite the bioRxiv website stating that review and hypothesis articles should not
494 be posted, and that “manuscripts that solely summarize existing knowledge or present
495 narrative theories are inappropriate” (<https://www.biorxiv.org/about/FAQ>). In contrast, 5.3 %
496 of articles in our non-deposited control group are review article types.

497 The median number of authors per paper is lower for articles deposited to bioRxiv than those
498 not; this is a somewhat surprising, as it may be logically inferred that the more papers an
499 author has, the more likely it is to be deposited as a preprint at the request/suggestion of one

500 of the authors. For the first and last authors of an article, US authors were found to be
501 overrepresented in the bioRxiv-deposited articles compared to non-deposited control articles,
502 which may partly be a result of bioRxiv being a US-based platform, as well as institutional
503 and/or funding policies in the US encouraging the deposition of preprints. Median academic
504 age for both groups was found to be similar for first authors, but last authors were slightly
505 younger in the bioRxiv-deposited group than the non-deposited group, indicating that
506 preprints may be a phenomenon driven more by the younger generation of scientists. Female
507 authors were found to be underrepresented compared to male authors for both groups,
508 although the imbalance was greater in the bioRxiv-deposited group than the non-deposited
509 group; of first authors in the bioRxiv-deposited group, only 29.9 % were female, falling to
510 18.0 % for last authors. The finding that female authors are underrepresented as authors in
511 biomedical fields in general is in agreement with previous research (e.g. Larivière et al.,
512 2013), however the mechanism by which female authors are even less well represented
513 amongst preprint authors is not clear. Similar findings were reported from a survey of authors
514 conducted by the Association for Computational Linguistics; whilst 31 % of total respondents
515 were female, only 12.5 % of those who state they always or often post to preprint servers were
516 female (Foster et al., 2017).

517 Model parameters for regression analysis on citation counts using 6, 12 and 24 month citation
518 windows are summarised in Table 2. Note that for regression analysis on citation data, our
519 sample sizes decreased as the citation window increased, due to the number of articles which
520 had a sufficient citation length within our period of analysis. Where values were missing (e.g.
521 when we were unable to determine the gender of an author), we removed both the bioRxiv-
522 deposited and matched non-deposited articles from our analysis, to maintain balance of
523 publication ages between groups. We interpret significance at the $p < 0.005$ level, following the
524 recommendations of Benjamin et al. (2018).

525 For all three citation windows, the bioRxiv-deposited status, IF, OA status, author count and
526 review article status were found to be significant predictors of citations. For 12-month
527 citations, the first author gender was also found to be a significant predictor, and for 24-month
528 citations the country of the first and last author (US or not US) were additionally found to be
529 significant predictors. First and last author academic age, and the gender of the last author did
530 not significantly predict citation counts in any of the citation windows.

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Table 2: Negative binomial regression output reporting effects of 11 explanatory variables on citation counts. Regression analysis was undertaken at 3 key time intervals: 6 months post publication, 12 months post publication and 24 months post publication. Values in bold indicate significance at the $p < 0.005$ level, following the recommendations of Benjamin et al. (2018).

Variable	6-month citations (N = 7,654)			12-month citations (N = 4,784)			24-month citations (N = 1,838)		
	B	β	p	B	β	p	B	β	p
Intercept	-1.193	-	<0.001	-0.000	-	0.996	1.200	-	<0.001
Deposited to bioRxiv	0.421	0.049	<0.001	0.422	0.015	<0.001	0.529	0.007	<0.001
IF	0.086	0.110	<0.001	0.088	0.036	<0.001	0.080	0.013	<0.001
OA	0.376	0.029	<0.001	0.356	0.008	<0.001	0.297	0.002	<0.001
Author Count	0.014	0.043	<0.001	0.012	0.013	<0.001	0.006	0.002	<0.001
Review Article	0.264	0.012	<0.001	0.347	0.005	<0.001	0.342	0.002	0.001
US First Author	0.012	0.001	0.862	0.125	0.004	0.066	0.436	0.005	<0.001
US Last Author	0.092	0.011	0.172	-0.038	-0.001	0.573	-0.406	-0.005	<0.001
First Author Academic Age	0.003	0.005	0.190	0.001	0.001	0.588	-0.006	-0.001	0.148
Last Author Academic Age	0.006	0.008	0.035	0.006	0.002	0.044	0.008	0.001	0.110
Female First Author	-0.082	-0.08	0.016	-0.135	-0.004	<0.001	-0.200	-0.002	<0.001
Female Last Author	0.022	0.002	0.573	-0.010	0.000	0.802	-0.063	-0.001	0.299

Table 3: Negative binomial regression output reporting effects of 11 explanatory variables on various altmetric indicators including tweets, blog feeds, media mentions, Wikipedia mentions and Mendeley reads. Values in bold indicate significance at the $p < 0.005$ level, following the recommendations of Benjamin et al. (2018).

Variable	Tweets (N = 12,054)			Blog Feeds (N = 12,054)			Media (N = 12,054)			Wikipedia (N = 12,054)			Mendeley (N = 12,054)		
	B	β	p	B	β	p	B	β	p	B	β	p	B	β	p
Intercept	1.328		<0.001	-2.637	-	<0.001	-2.507	-	<0.001	-3.974	-	<0.001	2.695	-	<0.001
Deposited to bioRxiv	0.656	0.006	<0.001	0.383	0.147	<0.001	0.219	0.017	0.001	0.304	0.258	0.003	0.558	0.002	<0.001
IF	0.103	0.010	<0.001	0.096	0.394	<0.001	0.143	0.115	<0.001	0.076	0.691	<0.001	0.101	0.004	<0.001
OA	0.454	0.003	<0.001	0.670	0.173	<0.001	0.957	0.049	<0.001	0.322	0.184	0.049	0.327	0.001	<0.001
Author Count	0.005	0.001	<0.001	0.007	0.072	<0.001	0.029	0.058	<0.001	0.013	0.285	<0.001	0.003	0.000	<0.001
Review Article	0.257	0.001	<0.001	-0.037	-0.005	0.763	-0.560	-0.016	0.002	0.436	0.144	0.066	0.777	0.001	<0.001
US First Author	0.052	0.000	0.316	0.247	0.094	0.016	0.425	0.032	0.005	0.183	0.154	0.408	0.146	0.001	<0.001
US Last Author	0.096	0.001	0.063	0.099	0.038	0.331	0.021	0.002	0.891	-0.231	-0.195	0.298	-0.008	0.000	0.848
First Author Academic Age	0.024	0.002	<0.001	0.015	0.0563	<0.001	0.011	0.010	0.066	0.030	0.286	<0.001	0.004	0.000	0.011
Last Author Academic Age	-0.008	-0.001	<0.001	-0.013	-0.057	0.001	-0.003	-0.003	0.599	0.004	0.036	0.677	-0.008	0.000	<0.001
Female First Author	-0.038	-0.000	0.116	-0.015	-0.005	0.767	0.237	0.017	0.001	-0.210	-0.167	0.059	-0.113	0.000	<0.001
Female Last Author	-0.031	-0.000	0.264	-0.096	-0.030	0.101	0.085	0.005	0.308	-0.065	-0.045	0.609	-0.070	0.000	0.003

537 By taking the exponent of the regression coefficient, $Exp(B)$, we calculate an Incidence Rate
538 Ratio (IRR) of bioRxiv deposition of 1.52 for a 6-month citation window. That is to say,
539 when controlling for all other explanatory variables, bioRxiv-deposited articles receive a
540 citation advantage of 52 % over non-deposited articles. The citation advantage increases to 53
541 % for a 12-month citation window, and to 70 % for a 24-month citation window. Our
542 regression analysis showed however, that several other characteristics of articles not related to
543 bioRxiv deposition status had large effects on citation rates, for example for each unit increase
544 in journal IF, citations increased by ~8-9 % in all citation windows, whilst an article being
545 OA increased citations by ~45 % for a 6 month citation window, although the effect appears
546 to reduce with time, only increasing citations by 35 % for a 24 month citation window.
547 These results clearly demonstrate that any attempts to quantify a citation advantage of a single
548 platform or repository such as bioRxiv need to carefully consider other factors influencing
549 citation counts in their analyses.

550 Model parameters for regression analysis on altmetrics are summarised in Table 3. For all
551 altmetric indicators investigated (tweets, blogs, mainstream media articles, Wikipedia
552 mentions, Mendeley reads), bioRxiv deposition status, IF and number of authors were
553 significant predictors of altmetric counts. OA status was additionally a significant predictor
554 across all altmetric indicators with the exception of Wikipedia mentions. Calculated IRRs
555 suggest that bioRxiv deposition has the largest impact on tweets – bioRxiv deposited articles
556 received 93 % more tweets when controlling for the set of explanatory variables than non-
557 deposited articles (47 % for blog feeds, 24 % for media mention, 36 % for Wikipedia
558 mentions, 75 % for Mendeley reads). As with our citation analysis, we do not aim to establish
559 a causative link between bioRxiv deposition and altmetric indicators, but nonetheless our
560 results show that bioRxiv-deposited articles are shared significantly more in online
561 communities than non-deposited articles, even when controlling for multiple factors related to
562 the article and its authorship.

563 Our regression results reveal several other interesting differences in the behaviour of altmetric
564 indicators for articles in biological sciences. For example, review articles are significantly and
565 positively correlated with numbers of tweets and Mendeley reads, but significantly and
566 negatively correlated with the number of media mentions. This may show that articles
567 reviewing and summarising previous knowledge are highly shared amongst networks of
568 academics, they are not deemed particularly ‘newsworthy’ in comparison to more original
569 research. With respect to author academic ages, both first author academic ages are found to

570 positively predict mentions in tweets and blog feeds, but conversely the last author academic
571 ages negatively predict mentions and tweets. Gender is found to have no significant effect on
572 tweets, blog posts and Wikipedia mentions, but the gender of the first author is a positive
573 predictor of news mention (articles with a female first author receive 27 % more mentions in
574 mainstream media), whilst the gender of the first and last author negatively predict Mendeley
575 reads. These are just a few examples of factors which show that individual altmetric indicators
576 represent activity of different online communities (a full investigation of which is outside the
577 scope of this study; see Haustein et al. (2015) and Didegah et al. (2018) for further discussion)
578 and should thus be considered in isolation (instead of, e.g., aggregated Altmetric.com scores)
579 in future studies attempting to understand the relationship between altmetrics and preprint
580 deposition behaviour.

581 **5. Conclusions**

582 We have found empirical evidence that journal articles which have previously been posted as
583 a preprint on bioRxiv receive more citations and more online attention than articles published
584 in the same journals which were not deposited, even when controlling for multiple
585 explanatory variables. In terms of citations, the advantage is immediate and long-lasting –
586 even after three years following publication, bioRxiv-deposited articles continue to accrue
587 citations at a higher rate than non-deposited articles. Our finding of a preprint citation
588 advantage is in agreement with previous research conducted on arXiv, suggesting that there
589 may be a general advantage of depositing preprints not limited to a single long-established
590 repository. More research is needed to establish the exact cause of the citation and altmetric
591 advantage. However, our results do not implicate a clear early access or quality effect in
592 driving this advantage, which may point to access itself being the driver. Further research
593 should dive deeper into understanding motivations of researchers to deposit their articles to
594 bioRxiv, for example through qualitative survey and interviews, which will shed light on
595 factors related to author bias and self-selection of articles to deposit.

596 We additionally investigated longitudinal trends in citation behaviour of preprints themselves,
597 finding that preprints are being directly cited regardless of whether they have been published
598 in a peer-reviewed journal or not, although there is a strong preference to cite the published
599 article over the preprint when it exists. Preprints are also shared widely on Twitter and on
600 blogs, in contrast to mainstream media articles and Wikipedia where published journal articles
601 still dominate, suggesting that there remains some reluctance to promote un-reviewed
602 research to public audiences. In the continuing online debates surrounding the value of

603 preprints and their role in modern scientific workflows, our results provide support for
604 depositing preprints as a means to extend the reach and impact of work in the scientific
605 community. This may help to motivate and encourage authors, some of whom remain
606 sceptical of preprint servers, to publish their work earlier in the research cycle.

607 **6. Acknowledgements**

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609 shortened ‘work in progress’ version of this work, entitled “Examining the citation and
610 altmetric advantage of bioRxiv preprints”, was submitted as a conference paper to be
611 presented at the 17th International Conference on Scientometrics and Informatics (ISSI 2019;
612 Rome, September 2-5, 2019).

613 **7. Author Contributions**

614 Conception and design: NF, FM, PM, IP. Acquisition of data: NF, FM. Analysis and
615 interpretation of data: NF, FM, PM, IP. Drafting and revising of article: NF, FM, PM, IP.

616 **8. Data Availability**

617 Data and code used for the analysis presented in this paper can be found at
618 <https://github.com/nicholasmfraser/biorxiv>.

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