

Why do scientists falsify data? A matched-control analysis

1 **Why do scientists fabricate and falsify data? A matched-control analysis of** 2 **papers containing problematic image duplications**

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16 17 **ABSTRACT**

18 It is commonly hypothesized that scientists are more likely to engage in data
19 falsification and fabrication when they are subject to pressures to publish, when they are
20 not restrained by forms of social control, when they work in countries lacking policies to
21 tackle scientific misconduct, and when they are male. Evidence to test these hypotheses,
22 however, is inconclusive due to the difficulties of obtaining unbiased data.

23 Here we report a pre-registered test of these four hypotheses, conducted on papers that
24 were identified in a previous study as containing problematic image duplications through
25 a systematic screening of the journal PLoS ONE. Image duplications were classified into
26 three categories based on their complexity, with category 1 being most likely to reflect
27 unintentional error and category 3 being most likely to reflect intentional fabrication.
28 Multiple parameters connected to the hypotheses above were tested with a matched-
29 control paradigm, by collecting two controls for each paper containing duplications.

30 Category 1 duplications were mostly not associated with any of the parameters tested,
31 in accordance with the assumption that these duplications were mostly not due to
32 misconduct. Category 2 and 3, however, exhibited numerous statistically significant
33 associations. Results of univariable and multivariable analyses support the hypotheses
34 that academic culture, peer control, cash-based publication incentives and national
35 misconduct policies might affect scientific integrity. Significant correlations between the
36 risk of image duplication and individual publication rates or gender, however, were only
37 observed in secondary and exploratory analyses.

38 Country-level parameters generally exhibited effects of larger magnitude than
39 individual-level parameters, because a subset of countries was significantly more likely to
40 produce problematic image duplications. Promoting good research practices in all
41 countries should be a priority for the international research integrity agenda.

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43 INTRODUCTION

44 The scientific literature is plagued by a small yet not negligible percentage of papers
45 with fabricated or falsified results. Survey studies suggest that 1-2% of scientists admit to
46 having consciously fabricated or falsified data at least once [1, 2], although the actual
47 percentage of fabricated papers might be just a fraction of the percentage of self-reported
48 misconduct, at least in the field of Psychology [3]. Direct assessments of the rate of
49 image manipulation in biology, however, suggest that between 1-4% of papers contain
50 problematic images, at least part of which is likely to result from intentional fabrication
51 [4, 5].

52 Multiple sociological, cultural and psychological factors are hypothesized to increase
53 the risk that scientists engage in scientific misconduct, and testing these hypotheses is a
54 matter of ongoing theoretical and empirical research. Particular attention has been paid to
55 four major factors:

56 - *Pressures to publish*: it is commonly suggested that scientists might engage in
57 scientific misconduct in response to high expectations of productivity and/or impact. This
58 concern has already guided numerous policies and initiatives aimed at discouraging
59 scientists from publishing too much and/or from pursuing high impact at all costs (e.g. [6-
60 8]). Pressures to publish may be higher and increasing in countries in which institutions
61 are evaluated based on their publication performance (e.g. United Kingdom's Research
62 Excellence Framework), and/or in countries in which career advancement is determined
63 by publications (e.g. tenure-track system in the United States of America) and/or in
64 countries in which high-profile researchers are rewarded with cash (e.g. reward policies
65 in China, see [9]). The pressures to publish hypothesis is supported by perceptions
66 reported in anonymous surveys [10, 11], but fails to predict the incidence of retractions
67 and corrections [12], historical trends of scientists' publication rate [13], and the
68 likelihood to report over-estimated effects [14].

69 - *Social control*: sociological and psychological theories suggest that individuals
70 are less likely to engage in misconduct when scrutiny of their work is ensured by peers,
71 mentors or society (e.g. [15]). An elaborate socio-economic hypothesis predicts that
72 mutual criticism and policing of misconduct might be least likely to occur in developing
73 countries in which academia was built on the German model, and might be most likely in
74 developed (i.e. highly regulated) countries with an Anglo-American (i.e. highly
75 egalitarian) academic culture [16]. Within teams, the social control hypothesis predicts
76 that mutual criticism is likely to be directly proportional to the number of team members
77 and inversely to their geographic distance, a prediction supported by studies on
78 retractions and bias in the literature [12, 17].

79 - *Misconduct policies*: a growing number of countries and/or institutions are
80 establishing official policies that define scientific misconduct and that regulate how
81 suspected cases can be identified, investigated and punished. These policies express the
82 rationale that clear rules and sanctions will have a deterrent effect on misconduct [18].
83 Countries differ widely in how they define and enforce misconduct policies, and it is
84 commonly suggested that the greatest deterrent effect would be obtained by misconduct
85 policies that are legally enforced e.g. [19].

86 - *Gender*: males are more prone to taking risk and more status-oriented than
87 females, and might therefore be more likely to engage in scientific misconduct [20]. This
88 hypothesis received some support by statistics about findings of misconduct by the US

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89 Office of Research Integrity [20]. However, other interpretations of these data have been
90 proposed [21] and gender did not significantly predict the likelihood to produce a
91 retracted or corrected paper, once various confounders were adjusted for in a matched-
92 control analysis [12].

93 Progress in assessing the validity of these hypotheses in explaining the prevalence of
94 misconduct has been hampered by difficulties in obtaining reliable data. A primary
95 source of evidence about scientific misconduct is represented by anonymous surveys.
96 These however are very sensitive to methodological choices and, by definition, report
97 what a sample of voluntary respondents think and are willing to declare in surveys –not
98 necessarily what the average scientist actually thinks and does [1, 3, 22]. Retractions of
99 scientific papers, most of which are due to scientific misconduct [23], offer a pool of
100 actual cases whose analyses have given important insights (e.g. [12, 23-25]). Results
101 obtained on retractions, however, may not be generalizable, because retractions still
102 constitute a very small fraction of the literature and by definition are the result of a
103 complex process that can be influenced by multiple contingent factors, such as level of
104 scrutiny of a literature, presence of retraction policies in journals, and the scientific
105 community's willingness to act [26].

106 An unprecedented opportunity to probe further into the nature of scientific misconduct
107 is offered by a recent dataset of papers that contain image duplications of a questionable
108 or manifestly fraudulent nature, i.e. Bik et al. 2016 [5]. These papers were identified by
109 direct visual inspection of 20,621 papers that contained images of Western Blots, nucleic
110 acid gels, flow cytometry plots, histopathology or other forms of image that were
111 published between the years 1995 and 2015 in 40 journals. Having been obtained by a
112 systematic screening of the literature, this sample is free from most limitations and biases
113 that affect survey and retraction data, and therefore offers a representative picture of
114 errors and/or misconduct in the literature – at least with regard to image duplications in
115 biological research. Descriptive analyses of these data have yielded new insights into the
116 rate of scientific misconduct and its relative prevalence amongst different countries.

117 We conducted a pre-registered analysis (osf.io/w53yu) of data from [5] to test, using a
118 matched-control approach, multiple postulated social and psychological risk factors for
119 scientific misconduct. Our analysis focused on the largest and most homogeneous
120 subsample of the original data set, i.e. N=346 papers with duplicated images identified
121 from a sample of 8,138 papers published in the journal *PLoS ONE*, between the years
122 2013 and 2014.

123 Image duplications included in our sample could be due to unintentional error,
124 questionable practice or outright scientific misconduct. Following the classification used
125 in [5], image duplications were grouped in three categories according to their complexity
126 and therefore their likelihood to result from scientific misconduct:

- 127 - *Category 1*: Simple duplications, in which the same image is presented twice to
128 represent different conditions, possibly due to accidental mislabeling (N=83).
- 129 - *Category 2*: Duplication with re-positioning, in which one image has been shifted,
130 rotated or reversed, suggesting some level of active intervention by the researcher
131 (N=186)
- 132 - *Category 3*: Duplication with alteration, in which figures contained evidence of
133 cutting, patching and other forms of substantive embellishment and manipulation
134 which betrays a possible intention to mislead (N=77).

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135 Category 1 duplications are most likely to due to error, whilst categories 2 and 3 are
136 likely to contain a mixture of errors and intentional fabrications. Therefore, if factors
137 predicted to affect scientific misconduct have any effect at all, such effects are predicted
138 to be most relevant in category 2 and 3 duplications and to have little or no effect on
139 category 1 errors.

140 For each paper containing duplicated images, we identified two controls that had been
141 published in the same journal and time period, and that contained images of Western
142 blots without detectable signs of duplication. We then measured a set of variables that
143 were relevant to each of the hypotheses listed above, and used logistic regression to test
144 whether and how these variables were associated with the risk of committing scientific
145 misconduct.

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RESULTS

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Figure 1 reports the effects in each category of duplication of each tested parameter (i.e. odds ratio and 95% confidence interval), grouped by each composite hypothesis, with an indication of the direction of effect predicted by that hypothesis. In line with our overall predictions, Category 1 duplications yielded a null association with nearly all of the parameters tested (Figure 1, green error bars), and/or yielded markedly different effects from Category 2 and Category 3 papers (Figure 1, orange and red bars, respectively). Sharp and highly significant differences between effects measured on the latter and the former duplication categories were observed for authors' citation scores and journal scores (Fig 1a), and for several country-level and team-level parameters (i.e. Fig 1 b-e). No significant difference was observed amongst gender effects, except for a tendency of Category 3 duplications to be more common amongst female authors (Fig 1f).

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Differences between effects measured on Category 2 and 3 duplications were not always consistent with our prediction that Category 3 duplications should exhibit the largest effect sizes. For example, the number of years of activity of the author was only significantly associated with Category 2 duplications (Fig 1a). In most cases, however, the confidence intervals of effects measured for Categories 2 and 3 were largely overlapping, suggesting that differences between Category 2 and 3 might be due to the smaller sample size (lower statistical power) achieved for the latter category. Overall, therefore, results of univariable analyses are consistent with our predictions and confirm the original assessment of the status of these categories suggested by Bik et al. (2016): Category 1 duplications are most likely to reflect genuine errors whilst Category 2 and 3 errors are most likely to reflect intentional manipulations. Hypotheses about determinants of scientific misconduct, therefore, are most directly testable on the latter two categories, which were combined in all subsequent analyses reported in the main text. A supplementary file reports all numerical results of all analyses reported in the main text as well as all robustness analyses obtained on each separate duplication category and on all categories combined (see SI).

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Results of univariable tests combining Category 2 and 3 papers together are in good agreement with the social control hypothesis (Fig 2c) and partial agreement with the misconduct policy hypothesis (Fig 2e). The gender hypothesis was not supported (Fig 2f). The pressures to publish hypothesis was not or negatively supported by most analyses. In agreement with some predictions, the risk of misconduct was higher in countries in which

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181 publications are rewarded by cash incentives (Fig 2b) and was lower for researchers with
182 a shorter publication time-span (i.e. presumably early-career researchers, Fig 2a).
183 Contrary to predictions, however, the risk of misconduct was lower for authors with
184 higher journal score (Fig 1a) and in countries with publication incentive policies that are
185 career-based and institutional-based, despite the fact that the latter are those where
186 pressures to publish are said to be highest [10].

187 Overall, country-level parameters produced effects of larger magnitude (Fig 2).
188 Indeed, we observed sharp differences between countries with regard to the risk of
189 duplication (Fig 3). Compared to the United States, the risk was significantly higher in
190 China, India, Argentina and other developing countries (i.e. all those included in the
191 “other” category, Fig 3). Multiple other countries (e.g. Belgium, Austria, Brazil, Israel,
192 etc.) also appeared to have higher average risk than the United States but the very small
193 number of studies from these countries hampered statistical power and thus our ability to
194 draw any conclusion. Germany and Australia tended to have lower risk than the United
195 States, but only Japan had a statistically significant lower risk (Fig 3).

196 To reduce the possible confounding effect of country, we performed secondary
197 analyses on subsamples of countries with relatively homogeneous cultural and economic
198 characteristics (Fig S1). Such sub-setting appeared to improve the detection of individual-
199 level variables. In particular, the risk of duplication appeared to be positively associated
200 with authors’ publication rate, citation score, journal score and female gender (Fig S1 a-h,
201 and see SM for all numerical results). These effects, however, were never formally
202 statistically significant in such univariable analyses.

203 Secondary multivariable analyses, however, corroborated all of our main results (Fig
204 4). A model that included individual parameters, as well as an interaction term between
205 number of authors and number of countries (in place of the country-to-author ratio, which
206 is not independent from the number of authors) and country-level parameters of
207 publication and misconduct policies suggested that the risk of misconduct was
208 predominantly predicted by country and team characteristics (Fig 4a). The risk was
209 significantly higher in countries with cash-based publication incentives, lower in those
210 with national misconduct policies, and grew with team size as well as with number of
211 authors, with the latter two factors modulating each other: for a given distance, larger
212 teams were less at risk from misconduct, as the social control hypothesis predicted (Fig
213 4a).

214 When limited to English-speaking and EU15 countries, multivariable analyses of
215 individual and team characteristics supported most theoretical predictions, suggesting that
216 misconduct was more likely in long-distance collaborations and amongst early-career,
217 highly productive and high-impact first-authors (Fig 4b). Female first authors were
218 significantly more at risk of being associated with Category 2 and 3 problems, a finding
219 that is inconsistent with the gender hypothesis. Analyses on the remaining subset of
220 countries yielded similar results (Fig 4c).

221 Almost identical results were obtained with a non-conditional logistic regression
222 model, consistent with the fact that our sample was homogeneous with regards to
223 important characteristics such as journal, methodology and year of publication. Results
224 obtained combining all three categories of duplications were largely overlapping with
225 those presented in the main text and would have led to similar conclusions (see all
226 numerical results in SI).

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228 **DISCUSSION**

229 To the best of our knowledge, this is the first direct test of hypotheses about the causes
230 of scientific misconduct that was conducted on an unbiased sample of papers containing
231 flawed or fabricated data. Our sample represented papers containing honest errors and
232 intentional fabrications of various degrees in unknown relative proportions. However, we
233 correctly predicted that Category 1 duplications would exhibit smaller or null effects,
234 whilst most significant effects, if observed at all, would be observed in Categories 2 and 3
235 (Fig 1). Support of this prediction retrospectively confirms that, as suggested by a
236 previous analysis of these data [5], Category 1 duplications are most likely the result of
237 unintentional errors or flawed methodologies, whilst Category 2 and 3 duplications are
238 likely to contain a significant proportion of intentional fabrications.

239 Results obtained on Category 2 and 3 papers, corroborated by multiple secondary
240 analyses (see SI), supported some predictions of the hypotheses tested, but did not
241 support or openly contradicted others:

242 - *Pressure to publish hypothesis*: partially supported. Early-career researchers, and
243 researchers working in countries where publications are rewarded with cash incentives
244 were at higher risk of image duplication, as predicted. However, countries having other
245 publication incentive policies had a null or even negative risk (Fig 1b). In further
246 refutation of predictions, individual publication rate and impact of authors was not or
247 negatively associated with image duplication, although in secondary multivariable
248 analyses we observed a positive association between publication rate of first authors and
249 risk of duplication. The latter finding might represent the first direct support of this
250 prediction, but should be verified in future confirmatory tests. The correlation with cash
251 incentives may not be taken to imply that such incentives were directly involved in the
252 problematic image duplications, but simply that such incentives may reflect the value
253 system in certain research communities that might incentivize questionable research
254 practices.

255 - *Social control hypothesis*: supported. In univariable analyses, only predictions
256 based on socio-cultural conditions of different countries were in large agreement with
257 observations (Fig 1c). However, when country characteristics were controlled and/or
258 adjusted for, we observed a consistent negative interaction between number of authors
259 and number of countries per author in a paper, which is in good agreement with the
260 hypothesis (Fig 4).

261 - *Misconduct policy hypothesis*: partially supported. Countries with national and
262 legally enforceable policies against scientific misconduct were significantly less likely to
263 produce image duplications (Fig 1e, Fig 4a). However, other misconduct policy
264 categories were not associated with a reduced risk of image duplication, and tended if
265 anything to have a higher risk. As noted above for publication incentive policies, we
266 cannot prove a cause-effect relationship. The presence of national misconduct policies
267 may simply reflect the greater attention that a country's scientific community pays to
268 research integrity.

269 - *Gender hypothesis*: not supported. In none of the main and secondary analyses did
270 we observe the predicted higher risk for males. Some of the secondary analyses might
271 have found an association between female authors and the risk of image duplication (Fig
272 4b). This latter finding, however, needs to be validated in future confirmatory studies.

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273 A previous, analogous analysis conducted on retracted and corrected papers had led to
274 largely similar conclusions [12]. The likelihood to correct papers for unintentional errors
275 was not associated with most parameters, similarly to what this study observed for
276 category 1 duplications. The likelihood to retract papers, instead, was also found to be
277 significantly associated with misconduct policies, academic culture, as well as early-
278 career status and average impact score of first or last author. Differently from what this
279 study observed on image duplications, however, individual publication rate was
280 negatively associated with the risk of retraction and positively with that of corrections
281 [12]. We hypothesize that at least two factors may underlie this difference in results.
282 First, analyses on retractions included every possible error and form of misconduct,
283 including plagiarism, whereas the present analysis is dedicated to a very specific form of
284 error or manipulation. Second, analyses on retractions are intrinsically biased and subject
285 to many confounding factors, because retractions are the end results of a complex chain
286 of events (e.g. a reader signals a possible problem to the journal, the journal editor
287 contacts the author, the author's institution starts an investigation, etc....) which can be
288 subjected to many sources of noise and distortion. Therefore, whilst on the one hand our
289 results may be less generalizable, on the other hand they are more accurate and less
290 biased than results obtained on retractions.

291 A remarkable agreement was also observed between these results and those of a recent
292 assessment of the causes of bias in science, authored by two of us [14]. This latter study
293 tested similar hypotheses using identical independent variables on a completely different
294 outcome (the likelihood to over-estimate results in meta-analysis) and using a completely
295 different study design. Therefore, the convergence of results with this latter study is even
296 more striking and strongly suggests that all these separate analyses are detecting genuine
297 underlying patterns that reflect a connection between research integrity and
298 characteristics of authors, team and country.

299 The present study has avoided many of the confounding factors that limit studies on
300 retractions, but could not avoid other limitations. An overall limitation concerns the kind
301 of image duplication analyzed in this study, which is only one of the many possible forms
302 of data falsification and fabrication that may occur in the literature. This restriction limits
303 in principle broad generalizations. However, as noted above, our results are in large
304 agreement with previous analyses that encompassed all forms of bias and misconduct [12,
305 14], which suggests that our findings are consistent with general patterns linked to these
306 phenomena.

307 Two other possible limitations of our study design made results very conservative.
308 Firstly, we could not ascertain which of the duplications were actually due to scientific
309 misconduct and which ones derived from honest error, systematic error or negligence.
310 Secondly, our individual-level analyses focused on characteristics of the first and the last
311 author, under the assumption that authors in these positions are most likely to be
312 responsible for any flaws in a publication. However, we do not know who, amongst the
313 co-authors of included studies, was actually behind the problematic duplication. Both
314 these limitations ought to increase confidence in our results, because they are likely to
315 have reduced the magnitude of measurable effect sizes. As our univariable analyses
316 confirmed, image duplications that are due not to scientific misconduct but to
317 unintentional error are unlikely to be associated with any factor (Fig 1). Similarly, if an
318 image duplication was not caused by its study's first or last author, then we simply would

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319 not expect the characteristics of first and last author to be associated with the likelihood
320 of that error. Therefore, to any extent that they affected the study, these two limitations
321 have introduced random noise in our data, reducing the magnitude of any measurable
322 effect and thus making our results more conservative.

323 Any random noise in our data might have reduced the statistical power of our
324 analyses, for the reasons discussed above. However, our statistical power was relatively
325 large. Even when restricted to the smallest subset (e.g. category 3 duplications) our
326 analyses had over 89% power to detect an effect of small magnitude. We can therefore
327 conclude that, despite the limitations discussed above, all of our tests had sufficient
328 power to reject null hypotheses for at least large and medium effect sizes.

329 A further possible limitation in our analysis pertains to the accuracy with which we
330 could measure individual-level parameters. Our ability to correctly classify the gender
331 and to reconstruct the publication profile of each author was subject to standard
332 disambiguation errors [27] which may be higher for authors in certain subsets of
333 countries. In particular, authors from South- and East- Asian countries have names that
334 are difficult to classify, and often publish in local journals that are not indexed in the Web
335 of Science and were therefore not captured by our algorithms. Any systematic bias or
336 error in quantifying parameters for authors from these countries would significantly skew
337 our results because country-level factors were found in this study - as well in previous
338 studies on retractions - to have significant effects [12]. However, all our main conclusions
339 are based on effects that were measured consistently in subsets of authors based on
340 countries at lower risk of disambiguation error. Moreover, this limitation is only likely to
341 affect the subset of tests that focused on author characteristics.

342 Indeed, this study suggests that significant individual-level effects might not be
343 detectable unless country-level effects are removed or adjusted for. This prominence of
344 country-level effects in determining the risk of problematic image duplications might be
345 one of the most important finding of this study. We observed clear and indisputable
346 evidence that problematic image duplications are overwhelmingly more likely to come
347 from China, India and other developing countries, consistent with the original
348 interpretation of these data [5]. Regardless of whether the image duplications that we
349 have examined in this study were due to misconduct or unintentional error, country-level
350 effects suggest that particular efforts might be needed to improve the reliability of studies
351 from developing countries.

352 Previous analyses on retractions, corrections and bias [12, 14] as well as the present
353 analysis of image duplications cannot demonstrate causality. However, all these analyses
354 consistently suggest that developing national misconduct policies and fostering an
355 academic culture of mutual criticism might be effective preventive measures to ensure the
356 integrity of future research.

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358

359 **MATERIALS AND METHODS**

360 Methods of this study very closely followed the protocol of a previous analysis of risk
361 factors for retractions and corrections [12]. To guarantee the confirmatory and unbiased
362 nature of our analyses, all main and secondary analyses as well as sampling and
363 analytical methodology were pre-specified and registered at the Center for Open Science
364 (osf.io/w53yu) [28]. The main goal of the analysis was to produce a matched-control

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365 retrospective analysis aimed at identifying which characteristics of papers and their
366 authors were significantly predictive of the likelihood to fall into the “treatment” as
367 opposed to “control” category (papers with or without problematic image duplications,
368 respectively).

369

370 *Sampling of papers*

371 Papers had been identified by the independent assessment of three of the present
372 paper’s authors (EB, AC, FF). Control papers were retrieved from the set of papers that
373 had been examined by the authors and in which no evidence of data duplication had been
374 recognized. For each treatment paper, two controls were retrieved for inclusion, i.e. one
375 published immediately before and one immediately after the treatment paper. Order of
376 publication was determined based on Web of Science’s unique identifier code. When the
377 candidate control paper of one treatment paper coincided with the candidate control of
378 another treatment paper, the next available control paper was selected instead.

379

380 *Data collection*

381 Following previous protocols[12, 14], we collected a set of relevant characteristics of
382 all included papers and of all of their authors. More specifically, for each paper we
383 recorded:

- 384 - Number of authors of each paper.
 - 385 - Number of countries listed in the authors’ addresses.
 - 386 - Average distance between author addresses, expressed in thousands of kilometers.
- 387 Geographic distance was calculated based on a geocoding of affiliations covered in the
388 Web of Science [29].

389 For each author of each paper in the sample we retrieved the following data from the
390 Web of Science:

- 391 - Year of first and last paper recorded in the Web of Science.
- 392 - Total number of article, letters and review papers authored or co-authored.
- 393 - Total number of citations received by all papers authored or co-authored.
- 394 - Field-normalized citation score.
- 395 - Field-normalized journal impact score.
- 396 - Proportion of papers authored or co-authored that appeared in the top-10 journals
397 of that author’s field.
- 398 - Author’s main country of activity, based on the address most commonly
399 indicated.
- 400 - Author’s first name. The combination of first name and country was used to
401 assign gender. The majority of gender assignments were made by a commercial service
402 (genderapi.com) but an attempt was made to identify the gender of unassigned names.
403 When neither approach could attribute an author’s gender reliably, gender was assigned
404 to the “unknown” category.

405

406 Country information was used to assign each author to the corresponding country-level
407 variable, using the following scheme:

- 408 - Publication incentives policies: i.e. cash-incentives to individuals (CN, KR, TU);
409 performance linked to individual’s career (DE, ES, USA); performance linked to

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410 institution's funding (AU, BE, NZ, DK, IT, NO, UK), based on classifications in
411 [30].

412 - Social control hypothesis: developmental state - German academic model (CN,
413 JP, KR); intermediate case (DE, SI, TW, ISR); regulatory state & Anglo-
414 American academic culture (US, UK), based on classification by [16].

415 - Misconduct policy: national and legally enforced (USA, DK, NO); national non-
416 legally enforced (UK, SW, FI, NL, DE, AT, AU, JP, CN, KR, CR, TN, ZA); local
417 (institutional) policies (ES, IL, FR, BE, CH, EE, LV, PL, CZ, HU, PE, GR, IN,
418 BD), data based on references in [12].

419 Although we collected information for all authors of the papers, we only tested
420 individual predictors measured on the first and last authors, positions that in biomedical
421 papers tend to be attributed to the authors that most contributed to the research, often in
422 the role of junior and senior author, respectively [31, 32].

423

424 *Analyses*

425 All variables were included in the analysis untransformed, although a few variables
426 were re-scaled linearly: author publication rate data was divided by 10, geographic
427 distance data was divided by 1000, and countries-to-author ratio was multiplied by 100.
428 This re-scaling of some variables served the purpose of improving the visibility of effect
429 sizes in figures and had no impact on the results.

430 All hypotheses were tested using standard conditional logistic regression analysis, i.e.
431 a logistic regression model with an added "stratum" term that identifies each subgroup of
432 treatment and matched controls. The conditional logistic regression approach is most
433 useful when papers differ widely in important characteristics, such as year and journal of
434 publication (see [12]). Analyses were also repeated with a non-conditional logistic
435 regression to assess the robustness of the results. Analyses were conducted with all three
436 categories of duplication combined, separately on category 1 and category 2 and 3 papers,
437 and combining categories 2 and 3.

438 Since the sample size was pre-determined, we did not conduct a prospective power
439 analysis. Post-hoc power analyses based on unconditional logistic regression suggest that
440 our main analyses, when combining papers from all duplication categories (a total of
441 1039 data points) had over 99% statistical power to detect a small effect size (i.e.
442 OR=1.5), and 89% power for analyses restricted to the smallest subsample, i.e. category 3
443 duplications. All analyses were conducted with the open-source statistical package
444 Survival implemented by the R software [33].

445

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447 study: DF; Collected data: RC, EB; contributed reagents and materials: EB, FF, AC;
448 analyzed data: DF; wrote the paper: DF with input from all authors.

449

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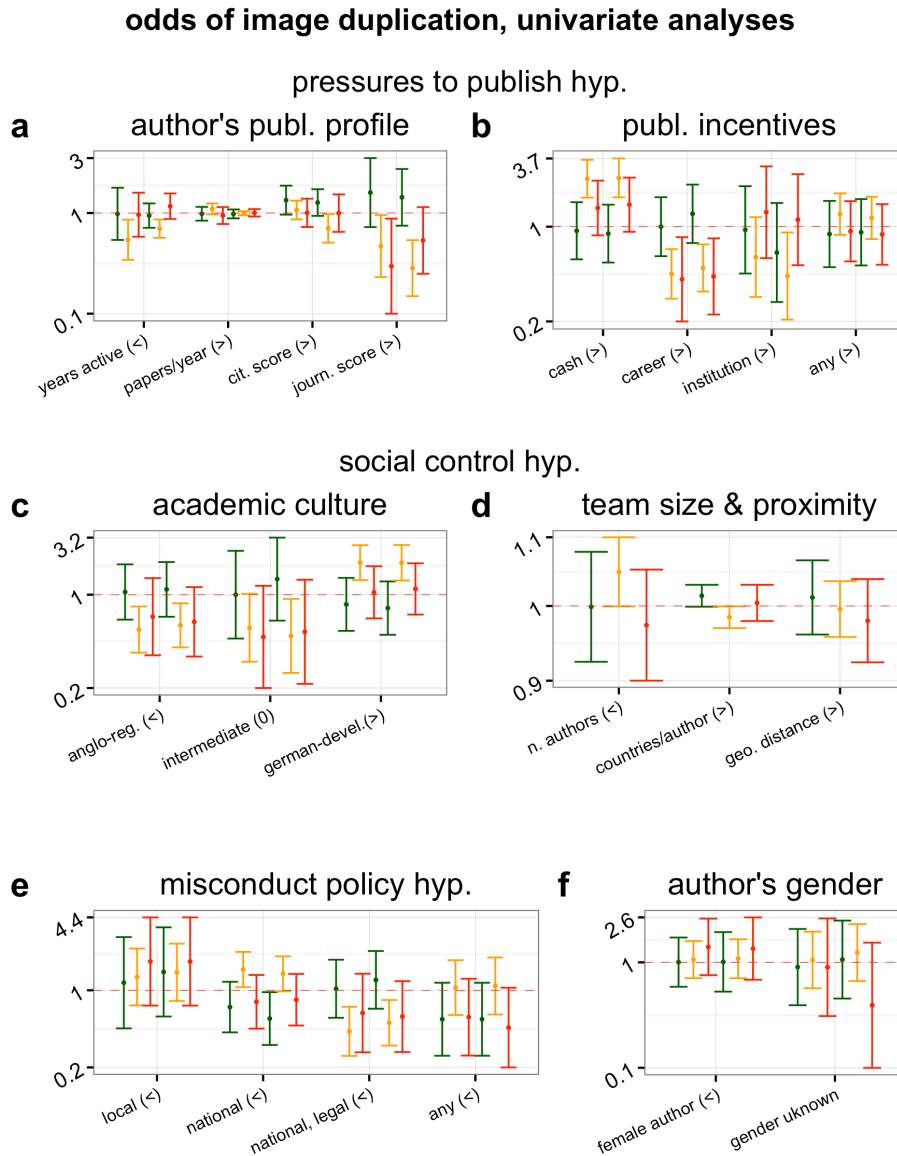
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554 **FIGURES**

555 **Figure 1**



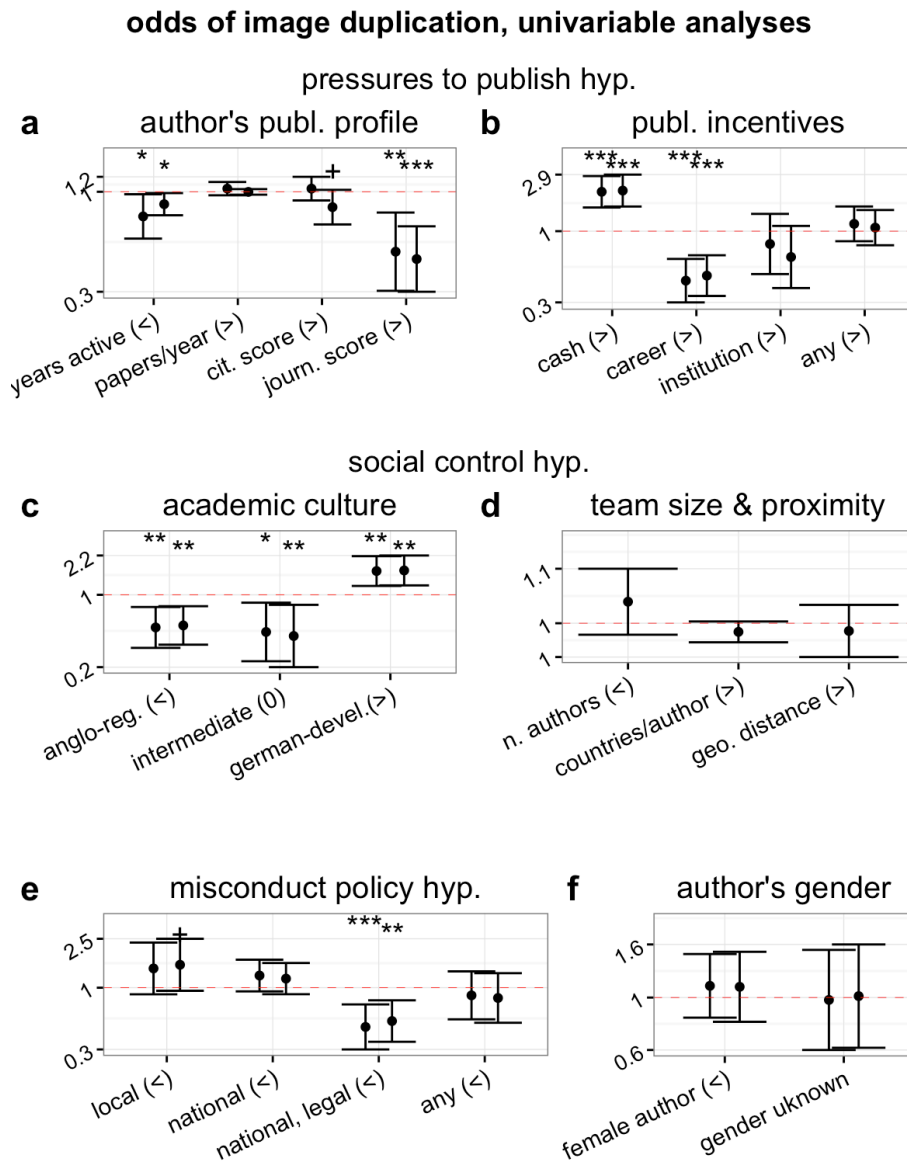
556

557 **Fig 1:** Effect (odds ratio and 95%CI) of characteristics of study and of first and last
 558 authors on the likelihood to publish a paper containing a Category 1 (green), Category 2
 559 (yellow) or Category 3 (red) problematic image duplication. When six error bars are
 560 associated with one test, the first three error bars correspond to data from the first author
 561 and the last three are for data from the last author. Panels are subdivided according to
 562 overall hypothesis tested, and signs in parentheses indicate direction of expected effect
 563 (“>” : OR>1; “<” : OR<1; “0”: intermediate effect predicted).

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564

Figure 2



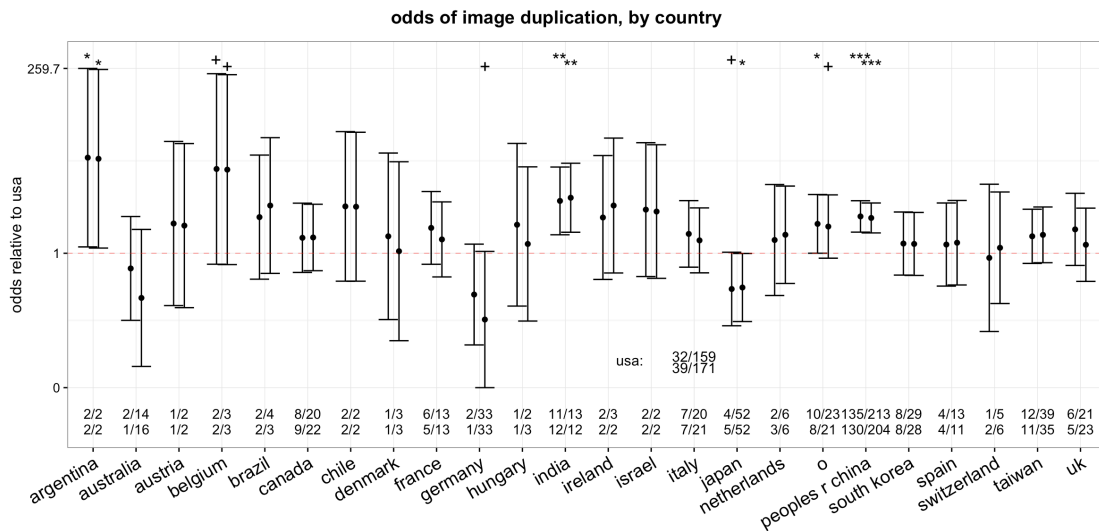
565

566 **Fig 2:** Effect (odds ratio and 95%CI) of characteristics of study and of first and last
 567 authors on the likelihood to publish a paper containing a Category 2 or 3 problematic
 568 image duplication. For each individual-level parameter, first and second error bars
 569 correspond to data from first and last authors, respectively. Panels are subdivided
 570 according to overall hypothesis tested, and signs in parentheses indicate direction of
 571 expected effect (“>” : OR>1; “<” : OR<1; “0”: intermediate effect predicted). Formal
 572 thresholds of statistical significance are added above each error bar to facilitate effect
 573 estimation (“+”: p<0.1; “*”: P<0.05; “**”: P<0.01; “***”: P<0.001).
 574

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575

Figure 3

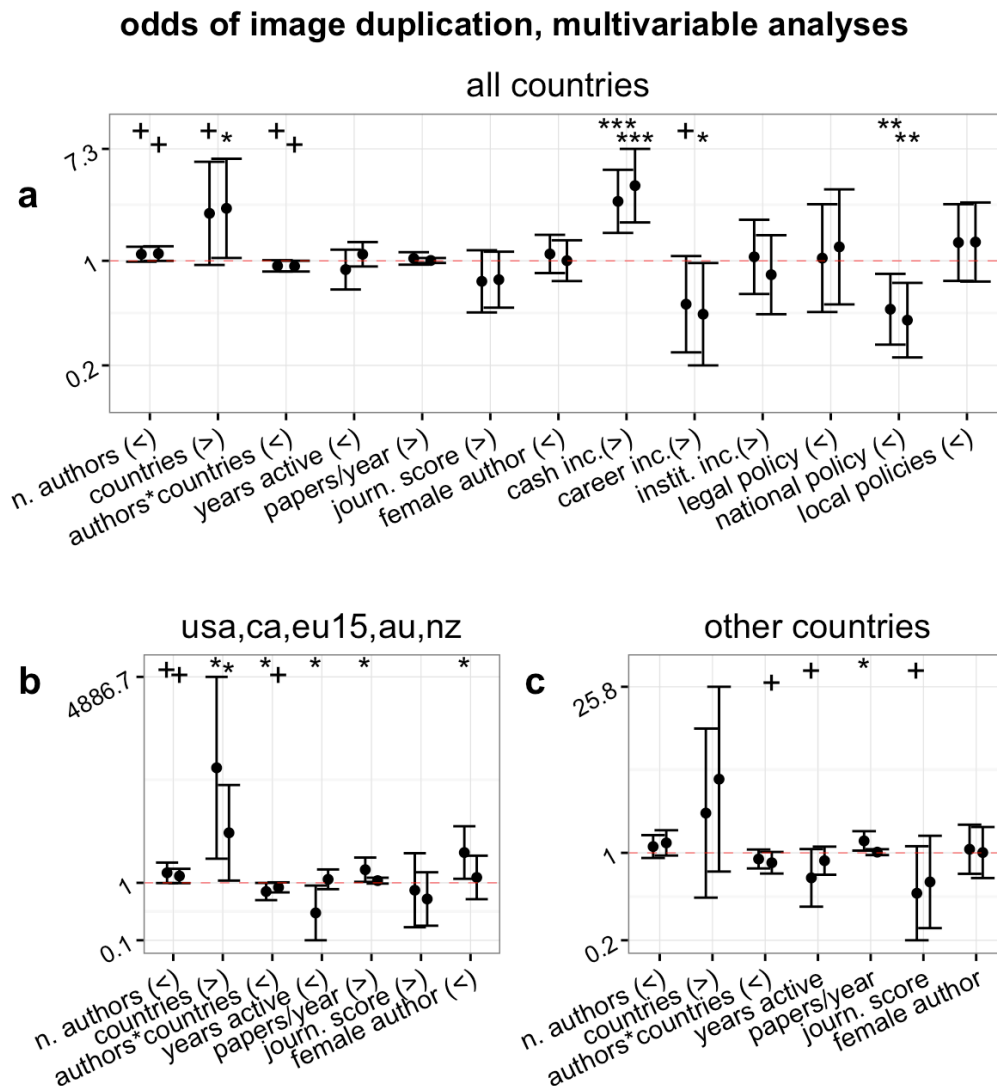


576

577 **Fig 3:** Effect (odds ratio and 95%CI) of country of activity of first and last authors on
578 the likelihood to publish a paper containing a Category 2 or 3 problematic image
579 duplication, compared to authors working the United States. The data were produced with
580 a multivariable logistic regression model, in which dummy variables are attributed to
581 countries that were associated with the first or last author of at least one treatment and
582 one control paper. All other countries were included in the “other” category. Numeric
583 data are raw numbers of treatment and control papers for first and last author (upper and
584 lower row, respectively). Formal thresholds of statistical significance are added above
585 each error bar to facilitate effect estimation (“+”: $p < 0.1$; “*”: $P < 0.05$; “**”: $P < 0.01$;
586 “****”: $P < 0.001$).
587

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588 **Figure 4**



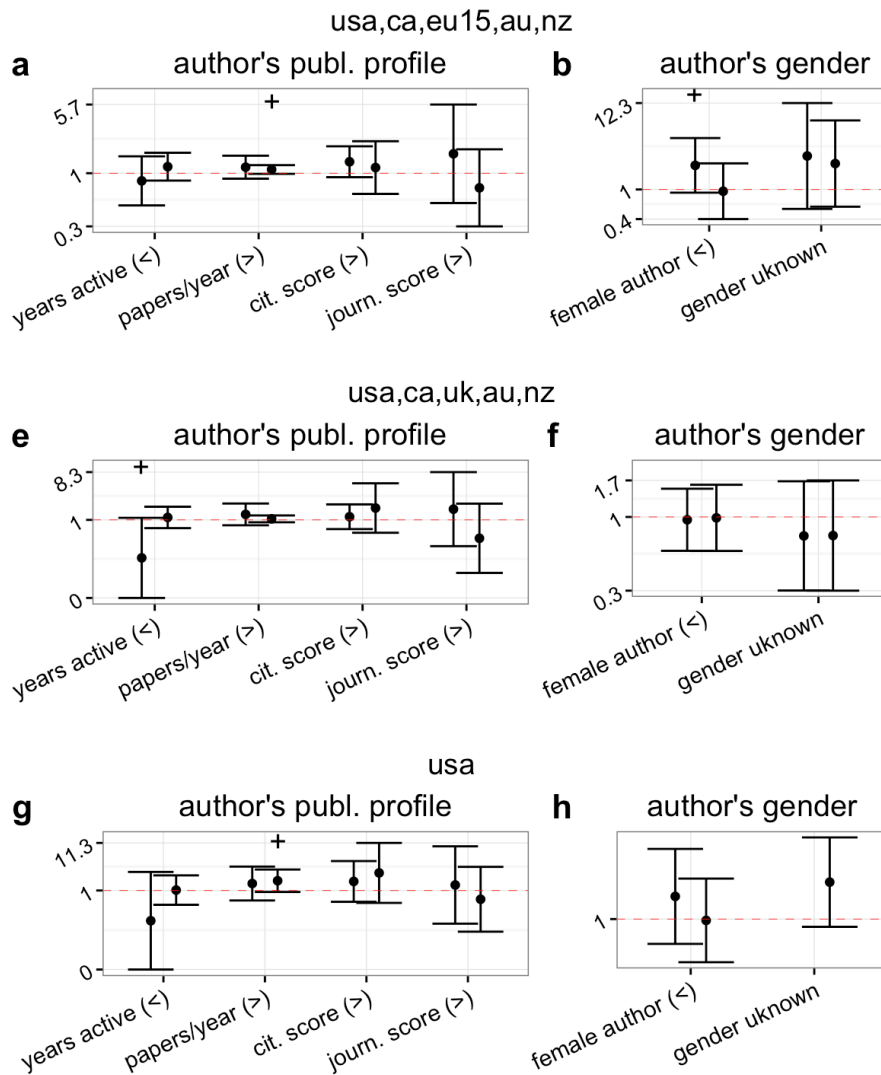
589

590 **Fig 4:** Effect (odds ratio and 95%CI) of characteristics of study and first and last
 591 author on the probability of publishing a paper containing a Category 2 or 3 problematic
 592 image duplication. Each subpanel illustrates results of a single multivariable model,
 593 partitioned by country subsets (see text for further details). First and second error bars
 594 correspond to data from first and last authors, respectively. Signs in parentheses indicate
 595 direction of expected effect (“>” : OR>1; “<” : OR<1). Formal thresholds of statistical
 596 significance are added above each error bar to facilitate effect estimation (“+”: p<0.1;
 597 “*”: P<0.05; “**”: P<0.01; “***”: P<0.001).

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598 **Figure S1**

odds of image duplication, subgroup univariable analyses



599

600 **Fig S1:** Effect (odds ratio and 95%CI) of characteristics of first and last author on
 601 probability of publishing a paper containing a Category 2 or 3 image duplication. Each
 602 subpanel shows results of univariable analyses on subsets of countries (see text for further
 603 details). First and second error bar correspond to data from first and last authors,
 604 respectively. Panels are subdivided according to overall hypothesis tested, and signs in
 605 parentheses indicate direction of expected effect (“>” : OR>1; “<” : OR<1). Formal
 606 thresholds of statistical significance are added above each error bar to facilitate effect
 607 estimation (“+”: p<0.1; “*”: P<0.05; “**”: P<0.01; “***”: P<0.001).