Research Article

The Consequences of Peer Review Bias for Academic Careers and the Progress of Science

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1. Independent researcher

A number of experiments and data have reproducibly demonstrated substantial peer review biases based on the prior reputations of individuals and institutions. For a given quality of research, papers coming from elite institutions and reputed authors have substantially higher chances of acceptance. This paper examines the downstream effects of peer review bias on the careers of individual researchers and on the global reach of science. Simulations show that when competition is high and publication metric is a major factor in reputation, a small bias in peer review escalates to a large difference in the scientific outputs from elite versus non-elite locations. It is likely therefore that PRB is largely responsible for the observed elitism and oligopoly in mainstream science. This hypothesis makes many predictions testable with scientometric data, some being already tested. Consequently, attempts to redesign science publishing in order to minimize publication bias is a necessary step towards more equitable global presence of science for humanitarian purpose.

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Introduction

The practice of peer review is considered mandatory for scholarly publishing today. However, it is not a time-tested custom. Although the principle is quite old, only a few journals practiced it[1]. Only in the late 20th century, mainly the 1970s, the practice was adopted by almost all journals[2][3]. The acceptance of the practice was not a result of an organized thoughtful collective decision but it spread more like an epidemiological process. It became established as a product of social evolution rather than a well-tested scientific principle. The efficacy and fairness of peer reviews was never put to rigorous test by sound

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experimental or analytical methods until recently. Nevertheless, it took roots so firmly that today peer review is believed to be irreplaceable and fundamental for science[4], ignoring the fact that a large number of revolutionary concepts including relativity, quantum mechanics, evolution, DNA structure became established in an era without mandatory peer reviews. Evidently peer reviews are not fundamental to science but their universal acceptance indicates that there is some adaptive value of peer reviews which resulted in their quick spread to fixation. A possibility is that in a peer review system editors can avoid authors' rage on rejection pushing the responsibility on someone anonymous. This social advantage to editors can be a main driving force leading to very quick adoption by editors. But any such hypotheses have not been examined by social scientists so far.

While talking about peer review bias (PRB) has largely been (and still is) a taboo over many decades[5], the assumption of fairness of peer reviews has been challenged by many studies recently[6][7][8][9][10][11][12][13]. The most direct demonstration of a large and inevitable peer review bias is by the experiment of Huber *et al*[8] which invited peer reviews on the same manuscript with a renowned verses obscure author name. The odds ratio for acceptance by prior author reputation turned out to be 6.23[10]. In other words there is a 523 % bias against obscure authors or institutions. Many studies show that the publication output from elite institutions is greater than non-elite institutions[14][15][16]. They think that the difference is explained by infrastructure, collegiality and larger teams, but they do not eliminate peer review bias as the possible cause[11].

Since the peer review practice grew as a social evolution, it is subject to the principles of human nature just like any other social traits. However, only recently the behavioral and social angles of scholarly publishing have been explored[9][10][17][18]. This is likely because scientists are generally treated as rational thinkers free from subtle innate aspects of human nature. This belief has never been supported by any research. In contrast there are studies showing counterintuitive subconscious human behavior even in an academic setting[19]. Education and research are two interconnected aspects of academia but in contrast to psychology of education, there is little research on the psychology of research and scholarly publishing. Human decision making has substantial contribution from system 1, which is innate, natural, fast and first response that comes with little conscious efforts as against system 2 that is slow, deliberate, conscious that comes with greater cost[20]. It is unlikely that scientists are free of this and other such fundamental psychological phenomena. Watve[9] suggests that rationalization, that is concocting justifications after having taken a decision[21] is likely to be common in peer reviews such that the true reasons for rejection and the justification given for it in the comments may not be identical. Cost benefit optimization is also a fundamental principle of decision making that is bound to influence editorial and reviewer decisions. Watve[9][10] suggests that many subconscious peer review biases can arise out of the innate evolved cost-benefit optimization algorithms. The cost benefits are context dependent and the system of working can influence the behavior by altering the cost-benefits. Therefore, it is possible to design a system that minimizes biases[22]. Although these insights in peer review bias are eye opening, they are still fragmentary and far from changing mainstream thinking and system design. Nevertheless, some remarkable but yet uncommon implementations of alternative peer review systems have been gaining recognition[23][24].

While research about evidence for PRB's presence, extent and possible remedies has picked up we address the other side of the issue in this paper, focusing on the possible consequences of PRB on the scientific community as well as on the progress of science. We develop a theoretical model here which does not aim to be a quantitative predictive model because many of the parameters remain unestimated as of now. But the model makes many qualitative predictions that are testable and can be important for arriving at a behavior optimized academic design[22] for better global science.

The model

We construct an individual based model that incorporates peer review bias, its effect on publication output in terms of number of papers as well as the journal prestige, the resultant reputation of the researcher, its effect on funding success, the effect of funding on downstream qualitative and quantitative research output. It is quite obvious that these factors work in an interconnected, cyclic and network fashion.

The model, at its baseline compares the net publication output of two researchers whose caliber and capacity is assumed to be equal but who are based in elite and non-elite institutions respectively. There is a small bias in peer review by the institutional reputation such that the probability of acceptance of a paper from the non-elite location is p and from the elite location as q such that $p < q$ by a bias factor b ranging from 0 to 1. $b.p = q$ so that at $b=1$ there is no bias. For comparative output from the model, we keep q constant at 0.9 and vary b.

At time zero the publishable work output of the elite W_{e0} and non-elite W_{n0} is assumed equal. Because the publication probabilities are slightly different, the publication output is $q.W_{e0} > p.W_{n0}$. The unaccepted MS,

W_{e0} - $q.W_{e0}$ and W_{n0} - $q.W_{n0}$ will be carried forward to the next time unit.

In the next time unit, we assume both will spend some time energy in revising and resending the rejected MS, from the one available for new output with a proportionality constant K_1.

Funding success depends at least partially on the recent publication output. Since funding success is a binary variable, we model the probability of funding as a function of recent publication output by a sigmoid curve whose parameters denote how important publication metric is to funding success, as well as the competition for funding.

$$F_{et} = \frac{\left(qW_{e(t-1)}\right)^a}{Ks^a + \left(qW_{e(t-1)}\right)^a}$$

Similarly for the non-elite

$$F_{nt} = \frac{\left(pW_{n(t-1)}\right)^a}{Ks^a + \left(qW_{n(t-1)}\right)^a}$$

Where F_{et} and F_{nt} are the probabilities of funding success for the elite and non-elite respectively at time *t*. *Ks* is the cutoff publication metric required for funding, expressed as the fraction of the metric of the top competitor in the field (W_{max}), if the metric was the sole criterion for success. Since it is not the sole criterion, some funding proposals below the threshold might also get success and some above may also fail, but the probability curve shows a point of inflection at *Ks*. *Ks* ranges between zero and one such that with increasing competition *Ks* will be closer to unity. The sharpness of the transition at *Ks* is decided by *a* (figure 1) so *a* represents the degree of dependence on the metric. With the probability of funding success defined this way, actual success is a stochastic event. The model assumes that multiple funding proposals can be submitted in one time unit but with a cost and an upper limit. If S_{et} *and* S_{nt} are the successfully funded projects respectively, for each successful attempt K_2 is the increase in publication output from the funded research.

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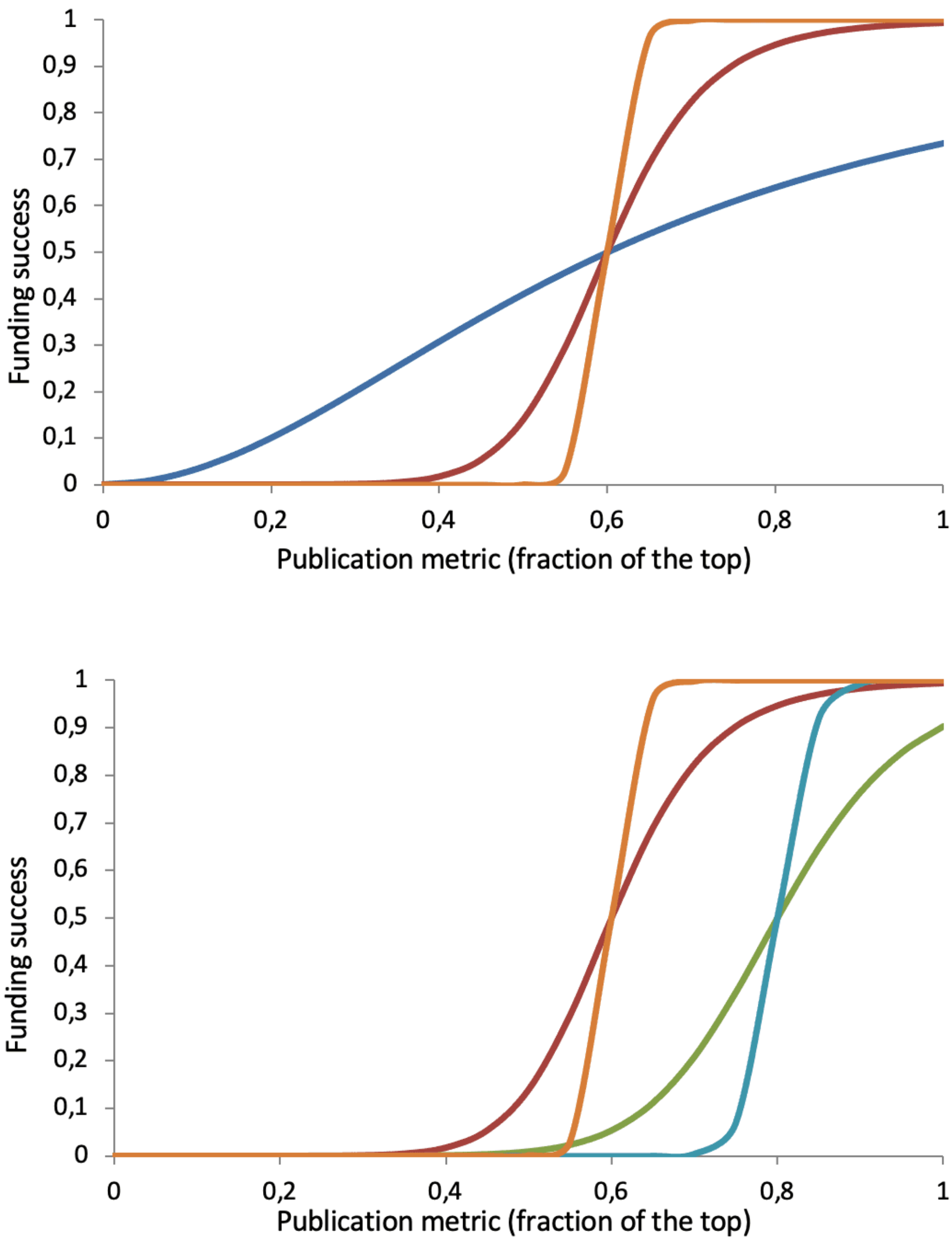

Figure 1. *Modeling the degree of dependence on publication metric and competition in funding success: The probability of funding success is a non-linear function of the prior reputation which is partially captured by the publication metric. The relevant publication metric of a researcher is expressed as the fraction of the maximum among the funding applicants. Since the capacity of funding agencies is limited and limited number of "best" proposals get funded, the relationship is sigmoid as captured by equation 1, where Ks denotes the severity of*

competition. The probability of success is 0.5 at Ks. It denotes the cut off for a sudden increase in the probability of success. The power parameter a (a >=1) denotes the degree of dependence on the metric. At small a the metric has limited importance in funding decisions. At large a the decision is mainly dependent on the metric. A. Effect of a on the success curve, a = 2 (blue), 10 (maroon) and 40 (orange) for the increasingly sharper curves. B. Effect of competition on funding success, Ks = 0.6 (orange and maroon curves) and 0.8 (green and blue curves) respectively with two curves representing a = 10 and 40.

Effectively the work output of the two researchers after time *t* would be a summation of (i) novel output of that time independent of funding (ii) the funding enhanced output during that time and (iii) previous unpublished carry forward. So we write,

$$W_{et} = W_i - K_1 \left(W_{e(t-1)} - q \cdot W_{e(t-1)}\right) + K_2 S_{et} + K_3 \left(W_{e(t-1)} - q \cdot W_{e(t-1)}\right)$$

And

$$W_{nt} = W_i - K_1 \left(W_{n(t-1)} - p \cdot W_{n(t-1)}\right) + K_2 S_{nt} + K_3 \left(W_{n(t-1)} - p \cdot W_{n(t-1)}\right)$$

Where W_i is the output independent of funding. K_3 <1 represents the down- gradation of the publication value of the papers owing to publication delays. This is most likely because rejected papers are often communicated to journals of lower impacts. The delay in publishing also makes it likely that someone else publishes similar findings first. Publication delay may also delay the further line of work. The net inclusive reduction in the value of the publication is represented by K_3.

This work output will result into publications for the year *t* by the probabilities *p* and *q* as above. And the cycle continues for subsequent time units. The model is used for simulations involving stochastic elements in two steps namely the probability of acceptance for every publishable output and probability of success of every funding proposal. All other calculations are deterministic. The published output of the 4th and 5th year combined is taken as the productivity of every researcher for further analysis.

Incorporating difference in individual capacity and individual reputation: The baseline model considers the individuals to have identical capabilities. Also individual reputation was not considered important in the peer review bias. The bias was assumed to be based on the institute's reputation. We now incorporate these factors by multiplying W_i, K_2 and F_t by the individual capacities C_e and C_n respectively, both ranging between zero and one.

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Apart from institutional reputation, we incorporate individual reputation as decided by the person's recent publication metric in comparison with the maximum in that field as $W_{(t-1)}/W_{max}$ and further assuming that the best of the two decides the publication bias. Further we can incorporate the difference in the infrastructure, collegiality, culture and supportive systems of elite and non-elite institutions by having D_e and D_n used along with C_e and C_n. This enables incorporation of individual reputation and institutional reputation separately in the simulations. The simulations examine how the individual and institutional reputations interact, and how the inevitable biases affect the research outputs of individuals with different capacities, reputations and locations.

Results

With the assumption of the baseline model that individuals with identical capacities are located in elite and non-elite institutions, we see that there is intricate interaction between research output, peer review bias, competition for funding and the degree of dependence on the recent publication metric (figure 2). If we assume no bias in peer review across institutions, the output of the researchers in 4^{th} and 5^{th} year down the line is not different as expected. The output follows more or less a normal distribution owing to purely chance factors. However, if the competition is too tough, and publication metric of significant importance in funding decisions, we see an interesting pattern emerging. The outputs become bimodal but still similar for elite and non-elite. The bimodality is a result of the vicious positive feedback loop between prior reputation and funding success. Individual researchers who get better publications by chance in their early careers, belong to the right-hand peak and the unfortunate ones in the left-hand peak. Apart from pure chance this is also likely to be decided by the reputation of the early mentors. The specificity of this bimodality to the context of severe competition and moderate to high dependence on publication metric indicates that chance or luck plays a major role in career success under conditions of tough competition and heavy reliance on publication metric. Luck has a marginal role and individual caliber mainly decides the career success when at least one of the two factors is of low intensity. When both are at high intensity, good or bad careers can be shaped largely by luck even when the individual researcher capacities, institutional support is assumed to be the same and there is no peer review bias.

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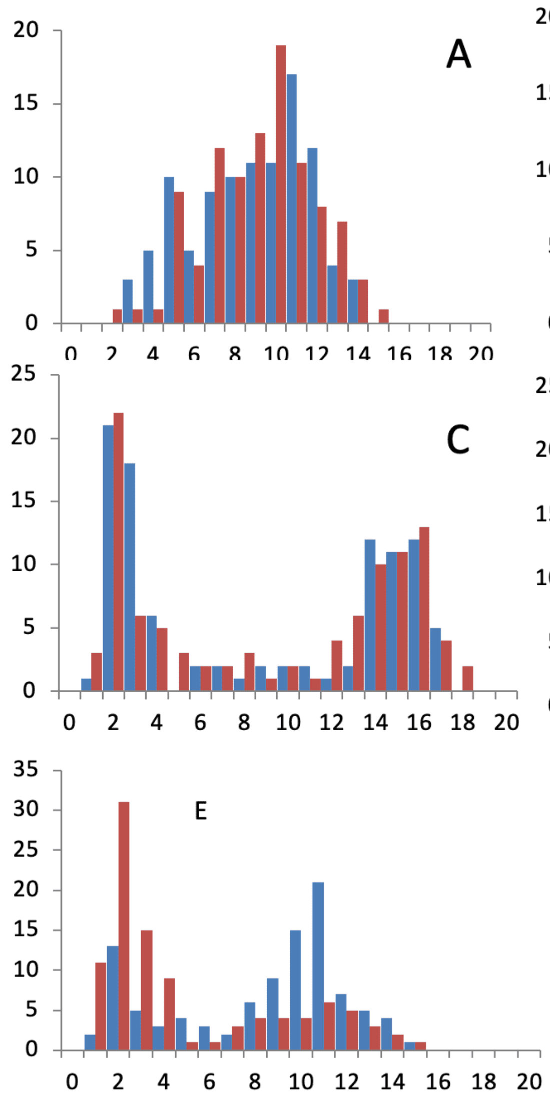

Figure 2. *The published research output (arbitrary units) predicted by the model from researchers of equal capability working in elite (blue bars) and non-elite (orange bars) institutions. A. When PRB is absent (b=1) and dependence on publication metric low (a=2) the output is comparable in spite of high competition (Ks = 0.95). B. Increased dependence on metric (a=8) but lower severity of competition (Ks =0.8) skews the distribution to the left. C. With severe competition (Ks =0.95) and high dependence on metric (a =8) there is bimodality indicating a strong role of luck in career paths. Still there is no mean difference in the elite and non-elite institutions. D. Introduction of 10% bias in peer review (a=0.8 and Ks=0.8) the output of elite and non-elite differ substantially. E. With the same bias, if competition is high (Ks = 0.95) the difference in output is disproportionately large with a distinct bimodality. F. With the same parameters as E, if dependence on the metric is reduced (a=2), the bimodality and difference in output vanishes. In short, PRB becomes a disproportionately serious problem only when competition and dependence on the publication metric is high.*

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Incorporation of a small peer review bias in the model makes a difference in the outputs of the elite and non-elite researchers. But when either the competition or the dependence on the prior publication metric is small, the difference is only proportional to the bias and often non-significant in stochastic simulations. When both competition and dependence on the metric increases, the difference grows out of proportion such that even a small bias in peer review leads to a large increase in the output ratio. This is due to the vicious cycle between low output-low funding.

Across the range of PRB it can be seen (figure 3) that the difference in output is a non-linear function of PRB. When both competition for funding and the degree of dependence on the publication metric is high, there is a threshold *b* over which the output ratio suddenly diminishes disproportionately. At low to moderate competition and dependence on metric, the output ratio is proportionate to PRB.

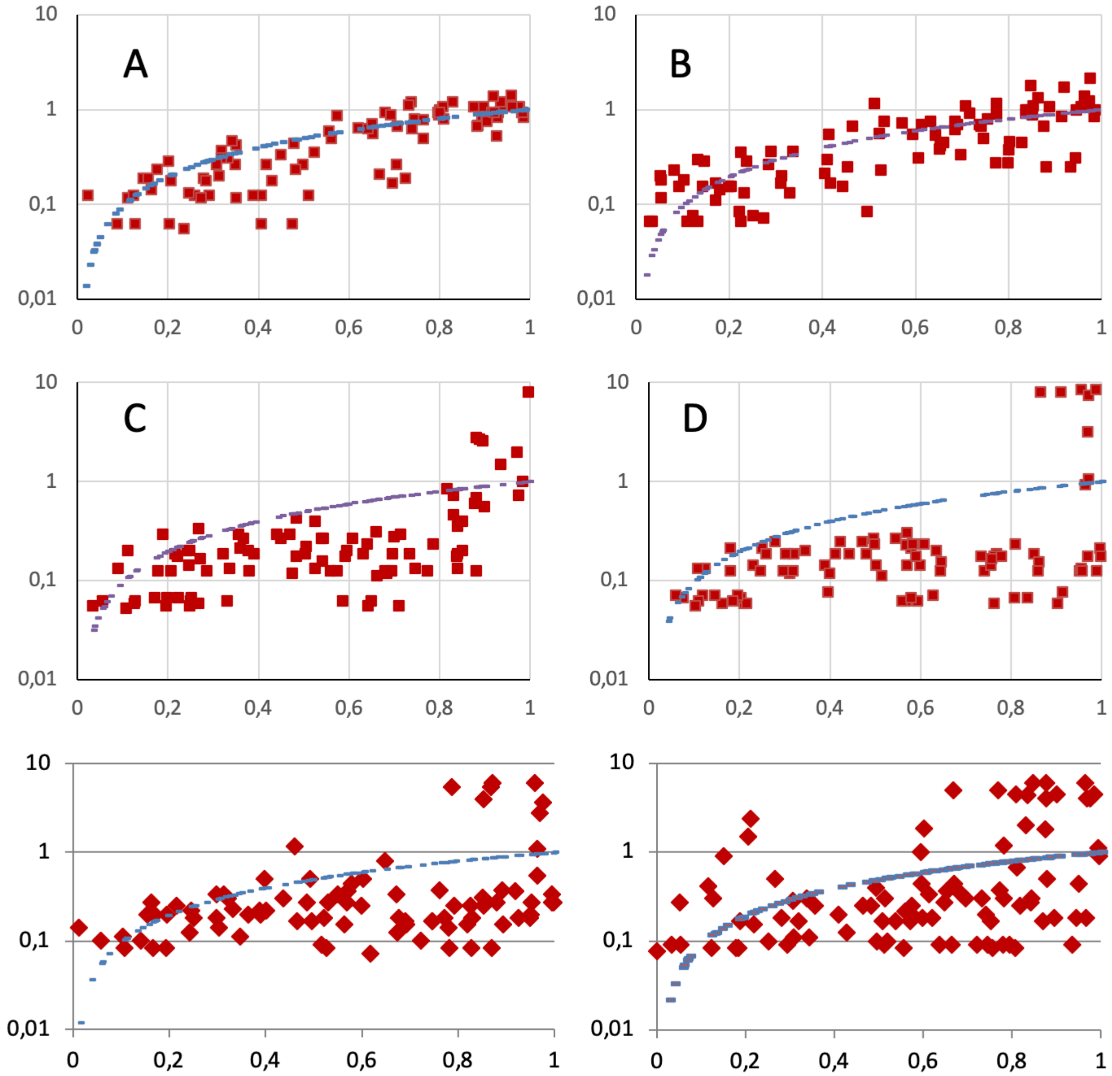

Figure 3. *How PBR (b) affects the ratio of outputs of the non-elite and elite researchers of equal caliber. PRB (represented by parameter b) on X and the publication ratio on Y axis. The red dots represent the ratios in stochastic simulations, blue line represents the ratio expected by PRB bias alone. A. When competition is low (Ks=.65) but dependence on metric is high (a=8) or B. competition is high (Ks=0.9) but metric dependence is low (a=2) the ratio is more or less proportionate to PRB. As both a and Ks increase, the ratio is disproportionately lower below a threshold b. C. at a =8 and Ks=0.8 D. at a=40 and Ks=0.9. E. When both individual and institutional reputation are incorporated, some individuals are able to retain high reputation and productivity in spite of being in a low reputation institution. F. When individuals shift from a higher to lower reputation institution and thereby starts with a higher individual reputation, some individuals are able to retain high productivity while others lose out by chance alone. The average productivity may be affected only marginally by the shift but variance increases. Note that in all simulations the*

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capacity of the elite and non-elite researchers is assumed to be identical. All the difference originates because of peer review bias or by chance alone.

When competition is intense and publication metric has a significant role in deciding funding success, researchers from non-elite institutions show much lower productivity than what can be directly explained by PRB. This is owing to a vicious cycle initiated by the PRB. In real life data it is difficult to segregate individual caliber, peer review bias and contribution of funding, infrastructure, group size and collegiality. Nevertheless, the model can help us in making differential testable predictions that are discussed in a subsequent section.

Optimization of novelty of work:

So far, we have assumed that the capacity or caliber of an individual is not affected by PRB and by institutional reputation. But let us now consider a different dimension of the problem in which the capacity itself might be reset. This thinking is based on the assumption that individuals optimize their own cost benefits at a fine scale and context specific optimization models have been suggested[9][10].

If we assume a conceptual scale of novelty of a piece of work it can scale from a small addition to information, conceptual novelty, questioning prevalent theory, disruptive and revolutionary. The probability of acceptance changes nonlinearly along this novelty scale. Minimum expectation from research is that it contributes something novel. Simultaneously there also exists some level of knowledge inertia, the resultant academic acceptance is expected to go in an inverted U shape because of the trade-off[24][25]. The inverted U shape is a result of two opposing forces namely novelty seeking and inertia, we need to ask the question how being from elite or non-elite institutions affects the two.

As an intrinsic part of behavior, editors and peer reviewers optimize their cost-benefits[9]. There is a time, energy and intellectual input cost in making an editorial decision. In addition, there is substantial reputation cost for a journal and thereby to the editors in publishing a low-quality paper. But there is little cost in rejecting a high-quality paper because this act remains confidential. The confidentiality prevents reputation loss from unfair rejections. Further use of proxies such as prior reputation of authors, geographic location from where it comes, the language related clues etc. reduces the cost of making a decision. Therefore, from individual cost benefit optimization point of view, it is beneficial to treat papers coming from reputed institutions with due care, but be careless while rejecting the ones coming from lesser institutions to save cost[9]. This can happen by human nature without any conscious intent to do injustice. By this principle, the required novelty is unlikely to be compromised even for an elite institution, but the inertia curve is most likely to differ. The shape and position of the inverted U as a net result can be substantially different for elite and non-elite (figure 4). Since individual researchers have an innate drive to optimize their own cost-benefits, they will attempt to achieve their specific optima. The long-term outcome of optimization would be that more novel, disruptive, revolutionary thinking is more likely to come from elite institutions while careers in non-elite institutions would be shaped better by being relatively mediocre along the novelty axis.

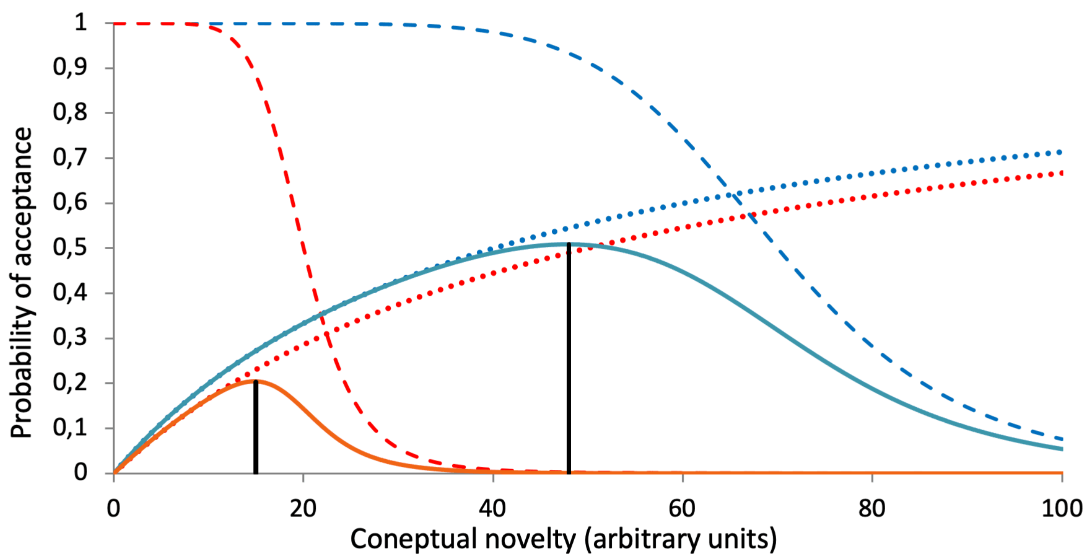

Figure 4. *Difference in novelty optima: The dotted lines represent the perceived positive effect of novelty on acceptance. The dashed lines represent inertia to accept novelty. Optimum novelty that can maximize success in an elite institute is substantially greater than that from a non-elite one. The difference is likely to arise from innate optimization in presence of PRB. If PRB can be removed, the gap between the quality of science coming from elite and non-elite locations is likely to reduce rapidly.*

There are further obvious parts of the dynamics that would increase inequality between elite and non-elite institutions. Researchers with higher caliber are more likely to join institutions of greater repute where their colleagues are more likely to be editors and reviewers of more prestigious journals, find better infrastructure and get brighter students. We did not incorporate these factors into the model since their qualitative effects are obvious. What the model demonstrates is that even in the absence of such factors, PRB alone can trigger a vicious cycle leading to large differences in the output.

Testable predictions and further line of work

Since publication process itself is biased, publication metric is not a reliable indicator of research output, individual caliber, capacity or creativity. There is no other objective source of data and therefore currently using the publication metric in some form or the other looks inevitable. Institutional affiliation appears to make a large difference in the publication output. The analysis by Chandra and Xu[16] shows that when researchers move from institutions of a lower to higher repute, their publication output increases. When they move from higher to lower, on the other hand, their output decreases but only marginally. They attribute the difference mainly to infrastructure and collegiality and do not even consider the possibility of publication bias being a causal factor. Since there are many independent demonstrations of publication bias[6][7][8][9][10][11][12][13], we need to consider it as a potential cause of the difference. The important question now is how much of the institutional difference is contributed by the different factors including individual researchers' calibers, peer review bias, institutional support of all kinds, collegiality, and competitive success in funding and the like. Separating the effects of these factors is a difficult task partly because they are interacting in a complex way and partly because publication metric is the only measurable index we have in hand which by itself is biased.

Nevertheless, certain patterns can be expected to emerge from the interaction between these complex factors. Based on these patterns certain questions can be addressed and certain hypotheses can be put to test. Some of them have already been tested, more predictions can be made and research can progress as follows.

1. Separating individual capacities from institutions is aptly done by Chandra and Xu[16] by quantifying the output of individuals who move between institutions. Their analysis establishes that independent of individual researcher's qualities, institutions make a difference for the publication outputs as in our model. They attribute the difference to collegiality and infrastructure, but their analysis does not rule out PRB. We suggest ways by which the effect of PRB can be separated from infrastructure and collegiality effects.
2. We can make a testable prediction that there would be a difference in the effect of inter-institutional migration based on the nature of work. For a kind of work that needs minimum infrastructure such as theoretical modeling, secondary data analysis, interpretive and synthesis kind of work, migration would make little difference if infrastructure or institutional support is the main cause. If peer review bias is the main cause, difference across fields is expected to be similar.

3. If collegiality is the main cause, with increasing ease of interactive communication across the globe, the difference should decrease. This could be tested by analyzing time trends in the institutional effects, which should show a decreasing trend in recent years.
4. If peer review bias and its consequences as modeled above are major causal factors, the institutional difference should increase with time as the competition and the reliance on publication metric increased in recent times.
5. Similar to shift in location, if a researcher shifts to work on a novel concept or a different field then the output from elite institutions should be affected much less than from a non-elite institution if peer review bias has a causal role.
6. Since quantitative data from publication record alone has its limitations, experiences, anecdotes and impressions of researchers are important. Well-designed opinion surveys would reveal whether and how frequently researchers have experienced peer review biases based on locations, prior reputations and other factors. In spite of the inevitable subjectivity of opinions these data would help in detecting prominent perceptions, generating novel possibilities and hypotheses if not conclusions.
7. Academia comprises an interaction between education and research. While there have been substantial inputs into the psychology of education, little inputs have gone into the psychology of research. Meta-science needs to move beyond publication data and add to pioneering fundamental work in the psychology and social dynamics of research. Evolutionary psychology of research is an almost entirely unexplored field that can play a significant role here.

We already have some patterns detected and published that document peer review bias[8][9], location effect on outputs[16], location and behaviors of editors and reviewers[12], behavioral optimization of editors and reviewers[9][10], the effect of publication metric on funding proposals[26], less citations when a person shifts to a new field[27]. However, at present these studies are fragmentary. More organized empirical work as well as synthesis efforts are needed to understand the dynamics of the interactions.

What we see today is dominance by a few elite institutions on the entire field, in which PRB is suspected to play a central role. The consequences of this oligopoly to global science have not been explored sufficiently well. But oligopoly is most likely to be a hindrance in the use of science for humanitarian purpose. A more equitable distribution of science over the globe would lead to a greater diversity of models of academia and different models have different advantages[28]. Therefore, steps need to be taken to make science more global, equitable and fair[29].

Conclusions

Simulations of the dynamics of the interactions between publication, funding, careers, infrastructure and locations show that as competition for publishing, funding and positions becomes intense and publication metric becomes a significant determinant in the competition, luck and early history of a researcher play an increasingly major role in shaping careers and productivity. A positive feed-back cycle operates between location, infrastructure, funding and publications because of which in a highly competitive system a small peer review bias leads to disproportionately large difference in productivity as well as novelty of the scientific outcomes. Peer review bias is likely to be the major cause of academic oligopoly. It is possible to empirically test the assumptions as well as predictions of the model. Measures to minimize peer review bias are likely to lead to globally more equitable distribution of scientific quality and productivity.

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