# Publish without Bias or Perish without Replications

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**Abstract**

There is mounting evidence that a large portion of experimental results cannot be replicated, leading many to believe that science is now in the throes of a replicability crisis. In response, there have been calls to reduce publication bias against negative results because of the effect that publication bias has on the publication record. Others, however, argue that publication bias need not be detrimental to scientific progress. Here, we propose a novel mechanism by dint of which reducing publication bias can benefit science regardless of the effect that publication bias has on the publication record. To do so, we introduce a series of increasingly complex mathematical models. Our models represent a scientific community consisting of discovery researchers who test novel hypotheses, and confirmation researchers who test known hypotheses. Results show that reducing publication bias can have the surprising consequence of increasing the share of confirmation researchers who conduct replications. When a large share of scientists conduct confirmation research, scientists have an incentive to conduct high-quality research as others are likely to check their findings. Our models therefore suggest an underappreciated reasons why reducing publication bias might benefit science.

## 1 Introduction

There is mounting evidence that a large portion of experimental results cannot be replicated. This is so across scientific disciplines, from the social and behavior sciences to biomedical and clinical research (Collaboration et al., 2015; Begley and Ellis, 2012; Camerer et al., 2016, 2018). As a result, many scientists report believing that science is now in the throes of a "replicability crisis" (Baker, 2016). If this is accurate, there are reasons to worry. On most accounts, failed replications are an indication that experimental protocols are unreliable (Machery, 2020; Romero, 2019). Although some argue that concerns may be overblown (Feest, 2019; Leonelli, 2018), there is a growing sense that something must be done in response.

Several proposals for improving replicability have already been made. A reward system based on the priority rule incentivizes the publication of new discoveries at the expense of replicability (Heesen, 2018; Romero, 2017). Changing the underlying incentives could therefore improve the overall quality of research. Another proposal is to invest in theory development, as the prior probability that a hypothesis is true can have a large effect on replicability (Ioannidis, 2005; Bird, 2020; Stewart and Plotkin, 2021). More controversially, some propose raising the usual standards of statistical significance (Benjamin et al., 2017)—but see McShane et al. (2019) for considerations against this approach. Unsurprisingly, expunging fraud and ethically questionable research practices might also boost replicability (Fanelli, 2009).

One proposal that has received a significant amount of attention is reducing publication bias. Also known as the "file drawer" problem (Sterling, 1959; Rosenthal, 1979), publication bias against negative results occurs when there is a preference for the publication of positive results—that is, results that seem to confirm a hypothesis of interest. Some argue that publication bias contributes to low replicability by increasing the share of false positives in the publication record and thus hindering the capacity of science to self-correct (Romero, 2016)—see also Greenwald (1975), van Assen et al. (2014), and Nosek et al. (2018). Others argue that publication bias is not necessarily a problem, as science might be able to self-correct even in the presence of publication bias (Bruner and Holman, 2019). Indeed, some even claim that abolishing publication bias entirely would be detrimental to scientific progress (de Winter and Happee, 2013).

Central to both camps in this debate is the effect that publication bias might have on the publication record: if publication bias harms science, it is because it skews the publication record. However, we argue in this paper that there is another mechanism by dint of which publication bias might be detrimental to science. To do so, we analyze a series of mathematical models loosely inspired by Romero (2018, 2020). Our models represent a scientific community consisting of discovery researchers who test novel hypotheses, and confirmation researchers who test known hypotheses. Following Zollman (2010), Holman and Bruner (2017), and O'Connor (2019), our models assume that the population undergoes evolution by cultural selection. Research practices from successful researchers are therefore more likely to spread, as others are more likely to adopt research practices of successful researchers.

Equilibrium and stability analysis yields a series of interesting results. First, we show that discovery and confirmation researchers can coexist in a population. This is so if researchers experience the effect of a competitive research environment, where resources for conducting research (funding, jobs, publishing opportunities, etc.) are limited and thus rewards are higher if there are fewer researchers of a given type in the community. Second, we show that a population of discovery and confirmation researchers cannot resist invasion by researchers who mix discovery and confirmation research. Finally, we explicitly consider the effect of publication bias on the population and propose a novel mechanism by dint of which reducing publication bias against negative results might benefit science. Reducing publication bias increases the relative incentive for confirmation research. Reducing publication bias can therefore increase the share of researchers who conduct replications, boosting replicability independently of the effect that publication bias has on the publication record.

The paper proceeds as follow. In Section 2, we describe and justify the model framework we use to evaluate this proposal. Building on this framework, we present a series of increasingly complex models in Sections 3, 4, 5, and 6. Analytical results show that discovery and confirmation researchers can coexist in a population provided that they experience the effect of a competitive research environment. Results also show that a population of discovery and confirmation researchers cannot resist invasion by researchers who mix between the two types of research. Surprisingly, results further show that reducing publication bias against negative findings can increase the share of confirmation researchers. In Section 7, we discuss the significance of these findings and suggest that promoting pre-registrations and pre-registered reports might be an efficient way to increase replicability. We conclude in Section 8 by noting some limitations of our approach.

## 2 The Credit Economy: A Framework

Models of the credit economy of science have become a common fixture in philosophy of science and social epistemology—for landmark papers and recent discussions, see Kitcher (1990), Strevens (2003), Weisberg and Muldoon (2009), Bruner (2013), Bright (2017), Zollman (2018), and Heesen (2019). There is also a long tradition in economics of building similar models—for examples, see Partha and David (1994) and Stephan (1996). A central assumption of these models is that scientists pursue not only epistemic goods, but also non-epistemic ones, such as credit (Merton, 1957, 1973). Credit in science comes in many different forms. But it usually includes the reputation, social status, awards, or number of citations that scientists receive for their research.

In keeping with such models, our framework assumes that scientists pursue credit when conducting research. Following Smaldino and McElreath (2016), O'Connor (2019), and Stewart and Plotkin (2021), we also suppose that scientists conduct research by testing hypotheses. If a test indicates that the hypothesis is true, we say that the result is positive; otherwise, we say the result is negative. Upon publishing a test result, the scientist receives some credit for their work.

Another assumption central to our framework is that the scientific community undergoes cultural evolution—for a similar approach, see also Zollman (2010), Holman and Bruner (2017), and O'Connor (2019). This means that we represent the scientific community as a population of scientists engaging in different research projects and that scientists choose what type of research to conduct by copying others. The choice of whom to copy is made on the basis of credit: not only are scientists more likely to copy colleagues with a high social status, but high-status scientists are also more likely to recruit and train students in research practices that yield more credit. In this way, the research profile of a scientific community can change over time.

Bringing together these assumptions, we let a scientific community change according to the following expression:

$$\dot{x}_i = x_i(w_i - \overline{w}) \tag{1}$$

where $x_i$ represents the frequency of scientists conducting research of type $i$, $\dot{x}_i$ represents the instantaneous rate of change in the frequency of scientists of that type, $\overline{w}$ is the mean value of $w_i$ over all types $i$, and $w_i$ is a function of the credit $c_i$ that a scientist of type $i$ receives for their research. These equations describe the replicator dynamics in an infinite population (Taylor and Jonker, 1978; Sandholm, 2010). An infinite-population model might be a good representation of large populations, such as modern-day scientific communities, but it is a well-known fact that the dynamics of an infinite population need not coincide with that of a finite population. In any case, $w_i$ represents the "cultural fitness" of the corresponding type. Here, cultural fitness measures how likely it is that a researcher of a certain type will give rise to researchers of the same type—either because a colleague chooses to imitate them, or because they train a student in the research practice of their choice.

In the next few sections, we build on this simple framework by introducing a series of increasingly complex models. These models represent important features of scientific communities, such as a competitive research environment and the advantage of opportunistic research. We analyze these models by first probing for their equilibrium states—that is, states of the population that are not subject to change. We then ask which of the available equilibrium states are stable in the sense that the population returns to that state after a small perturbation. Equilibrium and stability properties therefore tell us how a scientific community would change its composition under different initial conditions. This is important because the composition of a scientific community can play a role in replicability: when few scientists conduct confirmation research, few bother to check previous findings so there is little incentive for others to conduct high-quality research. Knowing what factors affect the composition of a scientific community can therefore help us understand what drives the replicability crisis.

# 3 Discovery and Confirmation Research

In keeping with the assumption that scientists conduct research by testing hypotheses (Smaldino and McElreath, 2016; O'Connor, 2019; Stewart and Plotkin, 2021), we start out by supposing that there are two types of researchers in the scientific community: discovery researchers, and confirmation researchers. Discovery researchers test novel hypotheses (hypotheses that have never been tested before), while confirmation researchers test known hypotheses (hypotheses that have already been tested at least once).

Of course, neither type of researcher knows for a fact whether the hypotheses that they test are true or false. All they have to go by are the test results that they obtain from their research. Given ample evidence of systematic bias in the publication record (Dwan et al., 2008, 2013), we assume that discovery researchers publish a test result only if it leads to a novel finding—that is, only if the result is positive (we relax this assumption later on). Confirmation researchers publish a test result whether it is positive or negative, as there are less incentives for only publishing positive results when replicating previous work.

Next, we let $c_N$ represent the credit that a discovery researcher receives for publishing a result that leads to a novel finding. Similarly, we let $c_R$ be the credit that a confirmation researcher receives for publishing a result—whether it is a positive result that confirms a previous finding or negative result that disconfirms it. We further assume that novel findings yield more credit per publication than replications, with $c_N > c_R$. This is because scientists generally prefer to publish a new discovery than a replication confirming or disconfirming a previously known result. At the same time, we suppose that discovery researchers publish at a lower rate than confirmation researchers. One reason for this is that confirmation researchers publish both positive and negative results, while discovery researchers only publish positive results. Another reason is that new discoveries are typically harder to come by than replications. We therefore let $p_N$ be the rate with which discovery researchers publish novel findings and $p_R$ the rate with which confirmation researchers publish replication studies, with $p_R > p_N$.

Expressing these assumptions in the framework of the replicator dynamics, the instantaneous rate of change in the frequency of discovery and confirmation researchers is given by:

$$\dot{x}_N = x_N(w_N - \overline{w}) \tag{2a}$$

$$\dot{x}_R = x_R(w_R - \overline{w}) \tag{2b}$$

where $x_N$ and $x_R$ represent the frequency of discovery and confirmation researchers, $\dot{x}_N$ and $\dot{x}_R$ represent the instantaneous rate of change in the frequency of these researcher types, $w_N$ and $w_R$ are the fitness functions of the corresponding researcher type, and $\overline{w}$ is the mean fitness of the population. For now, we let $w_N$ and $w_R$ be simply given by $w_N = c_N \cdot p_N$ and $w_N = c_R \cdot p_R$. Since we are considering a population composed entirely of discovery and confirmation researchers, the mean fitness is $\overline{w} = x_N \cdot w_N + x_R \cdot w_R$.

This is our simplest model. We analyze it by studying its equilibrium properties. Since $x_N = 1 - x_R$, it suffices to track the frequency of one researcher type. To find the equilibrium states, we determine the frequency of confirmation researchers when their frequency does not change. This can be done by setting $\dot{x}_R = 0$ and solving for $x_R$, which gives multiple solutions. For example, trivial solutions exist when $x_R^* = 1$ and $x_N^* = 0$ or, similarly, when $x_R^* = 0$ and $x_N^* = 1$. In both cases, the equilibrium state correspond to a state of the population in which only one type of researcher is able to persist (Figure 1).

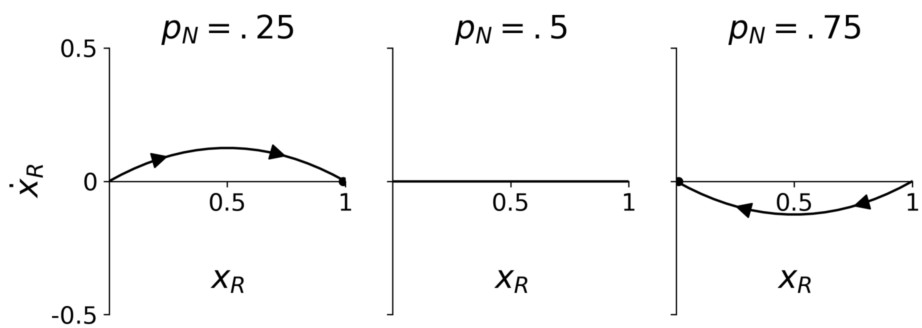


Figure 1: **Equilibria in a population of discovery and confirmation researchers.** Discovery and confirmation researchers cannot coexist at equilibrium. *Left:* when the publication rate for discovery researchers ($p_N$) is low relative to the publication rate for confirmation researchers, the population state with all confirmation researchers is the only stable equilibrium. *Center:* when the publication rate for discovery researchers is intermediate, any state is an equilibrium provided the population is indefinitely large (but not when the population is finite). *Right:* when the publication rate for discovery researchers is high, the state with all discovery researchers is the only stable equilibrium. Arrows indicate selection gradient; circles indicate equilibria. Shown are results for $c_N = 2$, $c_R = 1$, and $p_R = 1$.

Depending on fitness, both equilibria can be stable. When $w_R > w_N$, the dynamics carries the population to the equilibrium with $x_R^* = 1$. In this case, $\dot{x}_R > 0$ for all values of $x_N$ so that only confirmation researchers persist in the population. If a small number of discovery researchers enters the population, they are eventually driven to extinction due to the lower amount of credit that they receive. When instead $w_N > w_R$, the dynamics carries the population to the equilibrium with $x_R^* = 0$. In this case, only discovery researchers persist in the population. If we perturb the population by adding a few confirmation researchers, the lower amount of credit that they receive ensures that discovery researchers eventually outcompete confirmation researchers.

There is also a set of non-trivial solutions when $w_N = w_R$. In this case, discovery and confirmation researchers receive the same amount of credit so that selection cannot differentiate between them. In large communities that approximate the infinite population described by the replicator equations, this means that the frequency of both researcher types does not change: any value of $x_N^*$ or $x_R^*$ and thus any composition of the population is at equilibrium.

# 4 Academic Competition

We now assume that researchers experience the effect of negative frequency dependence. Negative frequency dependence means that selection for a particular type is inversely proportional to the frequency of that type in the population. In biology, it has long been known that selection for a particular type can decrease with the frequency of that type in the population (Allen and Clarke, 1984; Brisson, 2018). In our model, negative frequency dependence means that the more researchers of a given type there are, the lower the fitness of an individual researcher of that type. Negative frequency dependence is a plausible assumption in the highly competitive research environment of modern-day science: scientists must often compete for limited resources, such as funding, academic positions, and slots in journals and conferences (Kerr, 1995; Cyranoski et al., 2011; Schillebeeckx et al., 2013; Powell, 2015). Having more scientists conduct research of a certain type therefore decreases the amount of credit that individual scientists conducting that same type of research can receive.

There are of course multiple ways to represent negative frequency dependence. For simplicity, we assume that $w_N$ and $w_R$ decrease in direct proportion to the frequency of the corresponding researcher type. In particular, we let the fitness of both researcher types take the following form:

$$w_N = \frac{c_N \cdot p_N}{x_N} \tag{3a}$$

$$w_R = \frac{c_R \cdot p_R}{x_R} \tag{3b}$$

where the fitness of a type is high when the type is rare and low when it is common.

To consider the effect of negative frequency dependence in a population of discovery and confirmation researchers, we substitute expressions (3) for the corresponding terms in the replicator equations given by (2). This yields:

$$\dot{x}_N = x_N \left( \frac{c_N \cdot p_N}{x_N} - \overline{w} \right) \tag{4a}$$

$$\dot{x}_R = x_R \left( \frac{c_R \cdot p_R}{x_R} - \overline{w} \right) \tag{4b}$$

where the mean fitness of the population is defined as before but now simplifies to $\overline{w} = c_N \cdot p_N + c_R \cdot p_R$. So when researchers of a given type are rare in the population, their fitness goes up; when they are common, their fitness goes down. Negative frequency dependence therefore represents a low-rationality analog of rationally choosing the less frequency strategy when the less frequent strategy yields a higher payoff.

Again, it is enough to track the frequency of one researcher type since $x_N = 1 - x_R$. The equilibrium states are found by setting $\dot{x}_R = 0$ and solving for $x_R$. As before, there are two values that trivially satisfy this equality: $x_R^* = 1$, and $x_R^* = 0$. In both equilibria, discovery and confirmation researchers do not coexist in the population. But now these equilibria are not stable. If, say, a small number of confirmation researchers were to invade a population of discovery researchers, the invading confirmation researchers would face little competition from researchers of the same type. Initially, confirmation researchers would therefore receive a larger amount of credit than discovery researchers. The same is true if a small number of discovery researchers were to invade a population of confirmation researchers: initially, discovery researchers would receive more credit than confirmation researchers. With negative frequency dependence, there is always an advantage in being the less common researcher type.

There is also a non-trivial equilibrium. In this case, the equilibrium frequency of confirmation researchers is given by:

$$x_R^* = 1 - \frac{c_N \cdot p_N}{c_N \cdot p_N + c_R \cdot p_R} \tag{5}$$

where $x_N^* = 1 - x_R^*$. This non-trivial equilibrium is stable. When there are more discovery researchers than the equilibrium frequency, they have lower fitness than confirmation researchers; when there are fewer discovery researchers than the equilibrium frequency, they have higher fitness than confirmation researchers. In either case, there is an advantage in being the type with a frequency below what the equilibrium can sustain. This works against whatever researcher type is overabundant, which restores the equilibrium (Figure 2).

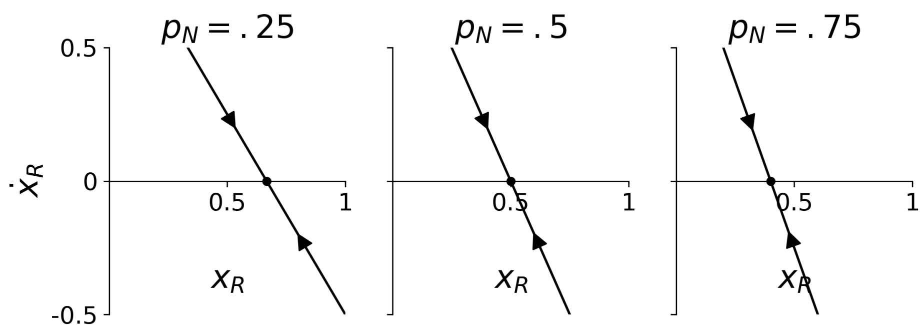


Figure 2: **Equilibria in a population of discovery and confirmation researchers with academic competition.** With negative frequency dependence, discovery and confirmation researchers can coexist at equilibrium. *Left:* when the publication rate for discovery researchers ($p_N$) is low, there are more confirmation than discovery researchers at equilibrium. *Center:* when the publication rate for discovery researchers is intermediate, there are as many confirmation as discovery researchers at equilibrium. *Right:* when the publication rate for discovery researchers is high, there are more discovery than confirmation researchers at equilibrium. Arrows indicate selection gradient; circles indicate equilibria given by equation (5). Shown are results for $c_N = 2$, $c_R = 1$, and $p_R = 1$.

When discovery and confirmation researchers experience the effect of negative frequency dependence, both researcher types can therefore coexist indefinitely in the population. At equilibrium, the exact distribution of discovery and confirmation researchers depends on the values of $w_N$ and $w_R$. When $w_N = w_R$, discovery and confirmation researchers coexist in the population at equal frequencies since $x_R^* = 0.5$. When $w_R > w_N$, both types of researchers coexist in the population but confirmation researchers outnumber discovery researchers ($x_R^* > x_N^*$). And when $w_N > w_R$, both researcher types again coexist but discovery researchers outnumber confirmation researchers

$(x_N^* > x_R^*)$.

If we suppose that our models represent a polymorphic population of pure strategists, these results hold only under the assumption that researchers cannot conduct both types of research. This assumption is very stringent. It requires confirmation researchers to be incapable of ever making new discoveries and discovery researcher to never do any confirmatory work. In the next section, we relax this assumption.

# 5 Opportunistic Research

In this version of the model, we introduce an opportunistic researcher type. Researchers of this type are opportunistic in that they mix the behaviors of discovery and confirmation researchers. Accordingly, we let $m$ be the probability that mixed-type researchers conduct discovery research, and $1 - m$ be the probability that they conduct confirmatory research. Otherwise, mixed-type researchers behave as other researcher types: they receive $c_N$ when publishing a novel finding at rate $p_N$, and they receive $c_R$ when publishing the result of a replication at rate $p_R$.

Researchers continue to experience the effect of negative frequency dependence. The fitness of each researcher type therefore depends on the frequency of that type in the population. However, the frequency of the mixed-type researcher now affects the fitness of each pure-type researcher differently. In particular, the fitness of the three researcher types is now given by:

$$w_N = \frac{c_N \cdot p_N}{m \cdot x_M + x_N} \tag{6a}$$

$$w_R = \frac{c_R \cdot p_R}{(1-m)x_M + x_R} \tag{6b}$$

$$w_M = m \cdot w_N + (1-m)w_R \tag{6c}$$

where $w_M$ represents the fitness of mixed-type researchers and $x_M$ is the frequency of that type. The fitness of all three researcher types therefore depends on the value of $m$.

Using the same framework as before, we substitute expressions (6) for the corresponding terms in the replicator equations (2). The dynamics of the population is now given by:

$$\dot{x}_N = x_N \left( \frac{c_N \cdot p_N}{m \cdot x_M + x_N} - \overline{w} \right) \tag{7a}$$

$$\dot{x}_R = x_R \left( \frac{c_R \cdot p_R}{(1-m) \cdot x_M + x_R} - \overline{w} \right) \tag{7b}$$

$$\dot{x}_M = x_M \left( m \cdot \frac{c_N \cdot p_N}{m \cdot x_M + x_N} + (1-m) \cdot \frac{c_R \cdot p_R}{(1-m) \cdot x_M + x_R} - \overline{w} \right) \tag{7c}$$

where $\dot{x}_M$ represents the rate of change in the frequency of mixed-type researchers. Although the mean fitness now includes terms for the three researcher types, notice that terms cancel out so that $\overline{w} = c_N \cdot p_N + c_R \cdot p_R$.

As the population is now composed of three researcher types, we find the equilibrium states by setting $\dot{x}_R = 0$ and $\dot{x}_N = 0$ and solving for $x_R$ and $x_N$ simultaneously. An equilibrium state is thus any pair of values $x_R^*$ and $x_N^*$ that solves both equations, with $x_M^* = 1 - x_N^* - x_R^*$. Solving for $x_R^*$ and $x_N^*$, we find a line of equilibria given by:

$$x_R^* = \frac{\overline{w}\,(m(1 - x_N^*) + x_N^*) - c_N \cdot p_N}{m\overline{w}} \tag{8}$$

where $x_N^*$ can take any value in the unit interval. Any point in the interior of this line represents a population consisting of not only discovery and confirmation researchers, but also mixed-type researchers. In any such equilibrium, there is no strict division of replication labor: some scientists conduct discovery or confirmation research exclusively, but others conduct both types of research (Figure 3).

There are trivial equilibria too: one equilibrium when $x_R^* = 1$, another when $x_R^* = 0$, and yet another when $x_M^* = 1$. These trivial equilibria differ with respect to their stability. The equilibrium where there are only confirmation researchers ($x_R^* = 1$) is unstable. A small number of discovery researchers can invade because they enjoy the advantage of being rare. For the same reason, mixed-type researchers can invade as well: by choosing a sufficiently high value of $m$, they reap the benefit of conducting the less frequent type of research. The equilibrium with only discovery researchers ($x_R^* = 0$) is likewise unstable. A few confirmation researchers can invade a population of discovery researchers, as confirmation researchers enjoy the advantage of being the less common type. Mixed-type researchers can also invade, as they receive the benefit of the less frequent research type if they

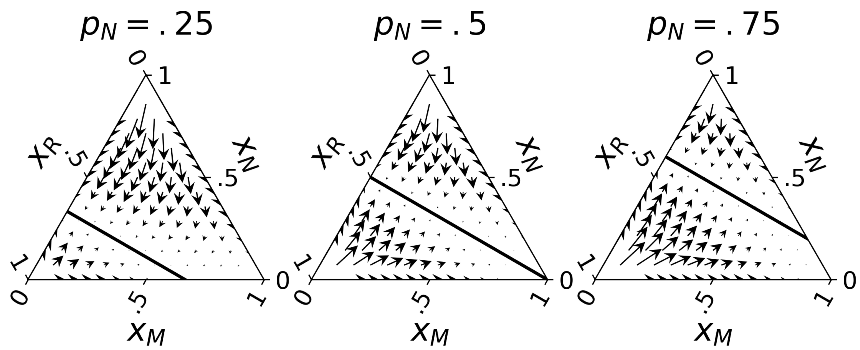


Figure 3: **Equilibria in a population with academic competition and opportunistic researchers.** With negative frequency dependence, discovery, confirmation, and opportunistic researchers can coexist at equilibrium. *Left:* when the publication rate for discovery researchers ($p_N$) is low, the equilibria sustain more researchers doing confirmation than discovery research. *Center:* when the publication rate for discovery researchers is intermediate, the equilibria sustain the same fraction of researchers doing confirmation as discovery research. *Right:* when the publication rate for discovery researchers is high, the equilibria sustain more researchers doing discovery than confirmation research. Arrows indicate selection gradient; lines indicate equilibrium states given by equation (8). Shown are results for $c_N = 2$, $c_R = 1$, $p_R = 1$, and $m = 0.5$.

choose an appropriately low value of $m$. Although there is a strict division of replication labor in these trivial equilibria, the equilibria are unstable.

But the equilibrium with only mixed-type researchers ($x_M^* = 1$) is neutrally stable. In this case, the population falls on the equilibrium line given by equation (8). If the population is shaken out of equilibrium along this line, the population is taken to another equilibrium state on the same line. For example, if a small portion of discovery and confirmation researchers were to enter a population of mixed-type researchers, the invaders might be able to persist depending on the exact ratio of discovery and confirmation researchers that arrive. Yet, the mixed-type researchers would do no worse than the invaders. Pure and mixed types would therefore coexist in a heterogeneous population.

# 6 Publication bias

This last model considers the effect of publication bias. Publication bias occurs when the result of a study—rather than its theoretical or methodological quality—biases the decision to publish it (Rothstein et al., 2006; Song et al., 2010). There is ample evidence for publication bias against negative results across scientific disciplines (Dwan et al., 2008, 2013). In the context of hypothesis testing, a positive result corresponds to rejecting the null hypothesis in favor of an alternative hypothesis of interest. Informally, a positive result thus corresponds to a new discovery. A negative result, on the other hand, corresponds to failing to reject the null hypothesis and the absence of a new discovery. Publication bias against negative results can therefore occur if journals prefer to publish positive over negative findings, or if scientists anticipate such a bias and are thus more likely to submit positive results for publication than negative results (Franco et al., 2014).

Whether the underlying mechanism for publication bias is due to journals' editorial preferences or authors' response to such preferences, we can model publication bias by supposing that scientists have different incentives to publish positive versus negative results and that scientists therefore publish positive and negative results at different rates. Accordingly, we assume that discovery researchers receive different amounts of credit for publishing positive and negative results. In particular, we let $c_N^+$ be the credit that a researcher receives for publishing a positive result and $c_N^-$ be the credit that they receive for publishing a negative result, with $c_N^+ > c_N^-$. We can now explicitly represent the strength of bias for positive over negative results. For simplicity, we do so by letting $b$ represent the share of publications that report a positive result, with $1-b$ corresponding to the share of publications that report a negative result. The parameter $b$ therefore ranges from 0 if only negative results are published to 1 if only positive results are published.

As before, $p_N$ is the publication rate for discovery researchers. Without the effect of negative frequency dependence, the credit that discovery researchers receive is $p_N \left(b \cdot c_N^+ + (1-b) \cdot c_N^-\right)$. The assumption of no frequency dependence is unrealistic in a competitive research environment, so we ignore this case. When there is negative frequency dependence, the credit that discovery researchers receive in a population consisting entirely of discovery and confirmation researchers is now given by:

$$w_N = \frac{p_N \left(b \cdot c_N^+ + (1-b) \cdot c_N^-\right)}{x_N} \tag{9}$$

where we assume no publication bias for confirmation researchers and the credit that confirmation researchers receive is thus $w_R = p_R \cdot c_R$, as before.

We now consider how publication bias alters the population dynamics with negative frequency dependence and pure types. To do so, recall that the corresponding population dynamics is given by equations (4). To find the equilibrium frequency of discovery researchers, we therefore substitute expression (9) into equations (4). Setting $\dot{x}_R = 0$ and solving for $x_R$ yields:

$$x_R^* = 1 - \frac{p_N \left(b \cdot c_N^+ + (1-b)c_N^-\right)}{p_N \left(b \cdot c_N^+ + (1-b)c_N^-\right) + c_R \cdot p_R} \tag{10}$$

where $x_N^*$ is the equilibrium frequency of confirmation researchers and $x_N^* = 1 - x_R^*$, as before. This equation is decreasing in $b$ provided that $c_N^+ > c_N^-$. The equilibrium frequency of confirmation researchers, $x_R^*$, is thus always decreasing in $b$ as long as discovery researchers receive more credit for positive than negative results. In a population of pure types and negative frequency dependence, publication bias against negative results therefore decreases the share of confirmation researchers at equilibrium (Figure 4).

Next, we consider how publication bias alters the population dynamics with negative frequency dependence and mixed-type researchers. The credit that discovery researchers receive in this case is given by:

$$w_N = \frac{p_N \left(b \cdot c_N^+ + (1-b)c_N^-\right)}{m \cdot x_M + x_N} \tag{11}$$

where the credit for mixed-type researchers is $w_M = m \cdot w_N + (1-m)w_R$.

In this case, equations (7) describe the population dynamics. To find the equilibrium states, we therefore substitute expression (11) into equations (7). Setting $\dot{x}_N = 0$ and $\dot{x}_R = 0$ and solving for $x_N$ and $x_R$, this yields:

$$x_R^* = \frac{\overline{w}\left(m(1-x_N^*) + x_N^*\right) - p_N \left(b \cdot c_N^+ + (1-b)c_N^-\right)}{m\overline{w}} \tag{12}$$

where $x_N^*$ can again take any value in the unit interval. Under the assumption that $c_N^+ > c_N^-$, this expression is also decreasing in $b$. So $x_R^*$ is decreasing in $b$ whenever discovery researchers receive more credit for a positive result than for a negative result. In a population of pure and mixed types with negative

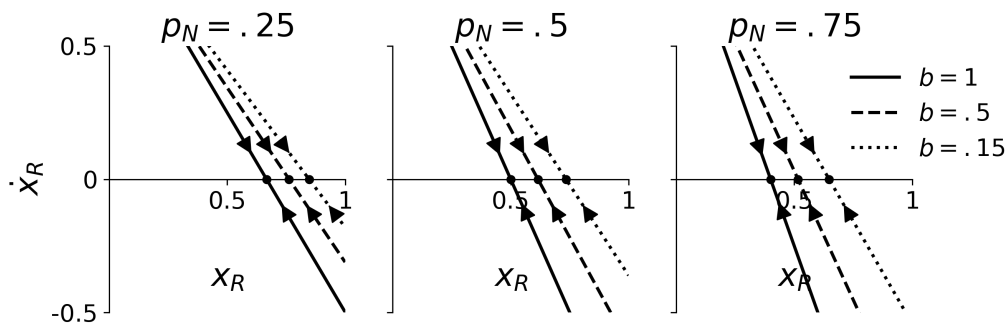


Figure 4: **Equilibria in a population of discovery and confirmation researchers with academic competition and varying levels of publication bias.** Decreasing publication bias ($b$) increases the share of confirmation researchers at equilibrium (*solid lines:* $b = 1$; *dashed lines:* $b = 0.5$; and *dotted lines:* $b = 0.15$) for different publication rates ($p_N$) among discovery researchers (*left*, *center*, and *right* panels). Arrows indicate selection gradient; circles indicate equilibria given by equation (10). Shown are results for $c_N^+ = 2$, $c_N^- = 0.5$, $c_R = 1$, and $p_R = 1$.

frequency dependence, publication bias against negative results again reduces the share of confirmation researchers at equilibrium (Figure 5).

In summary, increasing publication bias against negative results decreases the share of confirmation researchers at equilibrium. Equivalently, reducing publication bias against negative results increases the share of confirmation researchers at equilibrium. Intuitively, this is because reducing publication bias has an equalizing effect on the amount of credit that researchers of different types receive. Thus, reducing publication bias makes it easier for confirmation research to thrive when the credit economy would otherwise favor discovery research.

# 7 Discussion

In a series of increasingly complex models, we show that discovery and confirmation researchers can coexist in a population. This is possible if researchers experience the effect of a competitive research environment, where the credit that a scientist receives for their research depends on how many other scientists conduct research of the same type. We then show that a population of

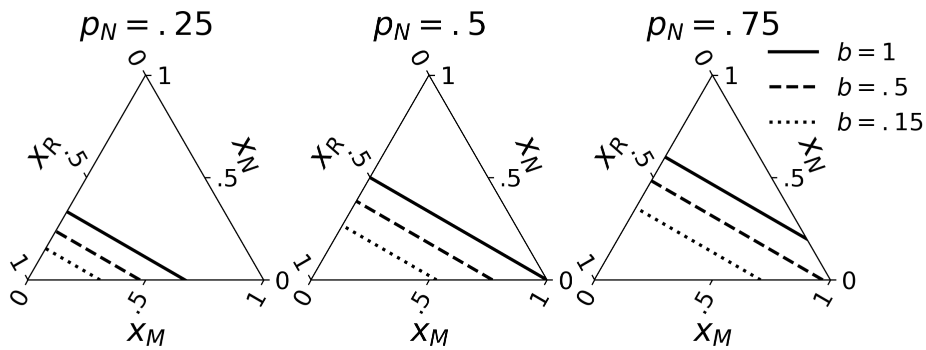


Figure 5: **Equilibria in a population with academic competition, opportunistic researchers, and varying levels of publication bias.** Decreasing publication bias ($b$) increases the share of researchers doing confirmation work at equilibrium (*solid lines:* $b = 1$; *dashed lines:* $b = 0.5$; and *dotted lines:* $b = 0.15$) for different publication rates ($p_N$) among those conducting discovery research (*left*, *center*, and *right* panels). Lines indicate equilibria given by equation (12); for clarity, selection gradient is not shown. Shown are results for $c_N^+ = 2$, $c_N^- = 0.5$, $c_R = 1$, $p_R = 1$, and $m = 0.5$.

discovery and confirmation researchers cannot resist invasion by researchers who mix discovery and confirmation research. Finally, we show that reducing publication bias against negative results increases the share of confirmation research at equilibrium.

Our results therefore suggest that mechanisms to reduce publication bias—for example, pre-registrations and registered reports—might be beneficial to science regardless of the effect that publication bias has on the publication record. Pre-registrations reduce publication bias against negative results by ensuring that researchers commit to a study design before knowing their results. When coupled with registered reports in which a study's methods are pre-registered and peer-reviewed before research is carried out, pre-registrations can also reduce publication bias by committing journals to publish a study whether results are positive or negative. That is, pre-registrations and registered reports reduce publication bias against negative results by decreasing the share of positive findings that discovery researchers publish (Wagenmakers et al., 2012; Nosek et al., 2018, 2019).

Independently of the effect that this may have on the publication record, reducing publication bias levels the difference in credit that discovery and confirmation researchers receive—especially when making discoveries is at a premium. With a smaller credit gap between discovery and confirmation research, the relative incentive to conduct replications goes up at the same time that the relative incentive to make discoveries goes down. By reducing publication bias, pre-registrations and registered reports therefore make scientists less averse to confirmatory work. This increases the share of confirmation researchers in the population, meaning that more scientists end up conducting replications and thus that there is additional pressure for others to conduct high-quality and reproducible research.

It is also worth emphasizing that reducing publication bias would not involve a large overhaul of existing methodological practices or the reward system of science. In fact, publishers can easily reduce publication bias by creating special tracks for registered reports, as many already do. Researchers should welcome the option to publish registered reports, as they are then guaranteed to publish their work no matter what results they obtain. Registered reports also seem to increase research quality (Soderberg et al., 2021), so journal editors should be eager to embrace the practice. For the same reason, science consumers and funding agencies should prefer research that comes out as registered reports. Reducing publication bias against negative results might therefore provide an effective response to the replicability crisis.

# 8 Conclusion

How should we respond to the replicability crisis? In this paper, we introduce and analyze a formal framework to address this question. Our framework allows us to describe a novel mechanism by means of which reducing publication bias—via pre-registrations and pre-registered reports—benefits science regardless of the effect that publication bias has on the publication record. In particular, we show that reducing publication bias against negative results increases the share of confirmation research at equilibrium. Reducing publication bias may therefore boost replicability if incentives for scientists to conduct high-quality research are higher when other scientists attempt to replicate previous results.

It is important to discuss some limitations of our approach, however. First, we restrict our attention to the distinction between discovery and confirmation research. Although science consists in a complex tangle of multifarious practices, it is helpful to focus on the distinction between these two types of research (Brandon, 1994; Steinle, 1997). This is because a closer look at the empirical evidence reveals that scientists do engage in discovery and confirmatory practices across disciplines (Franklin, 2005; Sakaluk, 2016). Our models therefore capture a crucial feature of scientific practice, even if other aspects—e.g. the distinction between manipulation and observation, among others—play an important role as well.

Second, we assume that scientists can conduct both discovery and confirmation research without incurring any cost for switching from one type of research to another. This is because meta-scientific work shows that scientists do in fact switch from one type of research to another, even though the quality of confirmatory research may go down when scientists attempt to confirm their own discoveries (Makel et al., 2012; Kunert, 2016). It is therefore a realistic feature of our models that the cost of switching from one type of research to another would have to be extremely high for scientists to not ever conduct both types of research. But it would be interesting to explicitly consider such a cost in further extensions of our model, as well as the possibility that scientists can spontaneously try out a different type of research.

More generally, it is important to highlight that the modeling approach we take here provides a "how-possibly" explanation (Dray, 1957; Grüne-Yanoff, 2013). That is, our models are silent on whether mechanisms that reduce publication bias—e.g. pre-registrations and registered reports—actually boost the share of confirmation research in real-world scientific communities and whether such mechanisms do in fact promote the use of high-quality research practices. Rather, our models allow us to isolate a mechanism that may or may not be instantiated in the real world. Although we believe that isolating this mechanism is a valuable endeavor on its own rights, it would be important to draw on the available empirical evidence and ultimately check whether such a mechanism operates in the real world—for example, by comparing the share of replications or other forms of confirmation research that journals with and without registered reports end up publishing. We leave treatment of this question for future work.


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