Social Dynamics and the Evolution of Disciplines

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Abstract

We consider the long-term evolution of science and show how a ‘contagion of disrespect’ – an increasing dismissal of research in subfields associated with marginalized groups – can arise due to the dynamics of collaboration and reputation (versus, e.g., preconceived notions of the field’s worth). This has implications both for how we understand the history of science and for how we attempt to promote diverse scientific inquiry.

1 Introduction

Why do scientific disciplines appear, disappear, merge together, or split apart? We might point to major events: the creation of new journals and departments, significant innovations, or new technologies. However, taking a social dynamics perspective, we can also note that at the heart of things is a social process involving interactions among

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individual scientists, deciding who to collaborate with and on what topic. While it is impossible to deny that big events play a role in shaping scientific inquiry, taking this social dynamics perspective allows us see how interactions among scientists give rise to broad, long-term trends in the evolution of science. Additionally, this perspective allows us to study the long-term effects of processes that are generally only studied in the short term, such as collaboration formation and reputation building.

As one instance of a broad historical trend, we will investigate the 'contagion of disrespect', whereby research in subfields associated with marginalized groups is increasingly dismissed as unimportant to the production of scientific knowledge (Schneider et al., 2022). While factors such as biased evaluation of work and institutional inequity surely play a role in this, we will show that collaboration dynamics are also likely part of the story. As explained in section 2, there is often unequal division of credit within collaborations according to social identity and a 'rich get richer' dynamic of credit received for the products of these collaborations. To show how these factors can shape broad patterns across scientific disciplines and give rise to a contagion of disrespect, we provide an agent-based model. We build on a previous model of the social dynamics of scientific disciplines, described in section 3, and add considerations of inequity, as described in section 4. Implications of these results will be discussed in section 5.

2 Contagion of Disrespect

The 'devaluation view' of labor in sociology of employment states that a change in the gender distribution of an occupation will lead to a change in the valuation of the work done (Levanon et al., 2009). There seems to be a similar devaluation in science. Further, Schneider et al. (2022) describe a contagion of disrespect, where new results in fields associated with marginalized groups are increasingly dismissed as unimportant to the production of scientific knowledge. Though this phenomenon is less well-studied than the devaluation view of labor, there are a few historical episodes that serve as ready examples.

First, as described by Schneider et al. (2022), Child Study, which studied infant cognitive development, arguably became less respected as women researchers took over. In the 1870s and 1880s, various well-respected 'men of science' like Darwin began publishing detailed accounts of their children's psychological developments, and encouraging others to do the same, leading to a booming interest in the field of Child Study. However, since women had easier access to children (because they were in charge of raising them), by the 1890s, scientifically-minded women like Millicent Shinn were compiling extensive notes and providing valuable findings. Correspondingly, the field diminished over the next 20 years and was eventually overshadowed by the field of experimental psychology (Lorch and Hellal, 2010; von Oertzen, 2013).

The history of computer science arguably shows both a contagion of disrespect and a reverse case, where respect increased as it became more male dominated. In the United States, before World War 2, male 'computers,' or what we would today call programmers, were given status as technical experts. During the war, however, women took over this role, and "With feminization came a loss of technical status" (Light, 1999, p. 460). As computer programming rose in popularity and importance during the war, it was overwhelmingly viewed as clerical work for women that freed male engineers from tedious calculations. It was considered less productive for knowledge or innovation than male-dominated engineering, even though it required the same understanding of the hardware as well as a high level of mathematical skill. Following World War 2, women were generally excluded from programming work and encouraged to be math teachers, or some such, instead (Light, 1999). Computer programming today enjoys correspondingly higher prestige than it did 70 years ago.

Though we do not have similar temporal data about changing demographic compositions, there are plenty of other fields where arguably a dismissal is/was due to their demographic composition. Just to name a couple: home economics, which among other things tied the kitchen to the chemical laboratory and allowed women to be professional academics (Stage and Vincenti, 1997), and indigenous ecology and forestry, where valuable work could have been integrated into other work on similar questions (Mason et al., 2012; Kimmerer, 2013). In what follows, we will tend to use the term 'devaluation' to refer to the general phenomena of scientific fields being dismissed due to their demographic composition, while referring to cases where such fields are increasingly dismissed over time as instances of a contagion of disrespect. (Though, as might already be apparent, we will use the terms 'field' and 'discipline' interchangeably.)

Studying the contagion of disrespect is important. We stand to lose a lot if entire areas of scientific research are dismissed, not because of any defect in their results, but because of their demographic composition. So, how do we explain the devaluation of work in these and other fields? One could appeal to particular roadblocks that exist or existed in the past, such as lack of institutional access. While those barriers are certainly an important part of the story, we want to show that, also, the social dynamics surrounding collaboration can lead to the devaluation of certain fields. Studying these dynamics allows us to look beyond particulars to see how (some) present reasons for devaluation are both continuous with the past and likely to continue into the future. Of course, here we are focusing on academic collaborations, but this viewpoint can apply more broadly.

3 The Social Dynamics of Science

Sun et al. (2013) provide an agent-based model to explore how collaboration dynamics can shape broad patterns across scientific disciplines. The basic idea is that as scientists go about collaborating and producing research, they create a network structure which captures how different scientists are connected to each other. As an overview, in each round of a simulation, there are three stages:

1. *Publication*: A new paper is published by a scientist, possibly with co-authors
2. *Growth*: There is some probability a new scientist enters the network
3. *Landscape change*: There is some probability fields merge together or split apart

The model starts with one scientist writing one paper. Then, as new scientists enter the community, they enter into their own collaborations and the network builds up from there. We will go through the above three stages in more detail now.

Publication: First, a new paper is published. A scientist, chosen uniformly at random from those in the network, is one of the authors and may or may not add co-authors to the paper. To capture the observation that people are more likely to collaborate with people they have more frequently collaborated with in the past, adding co-authors is done via a biased random walk. That is, when an author writes a paper, with probability p_w the walk stops and no co-authors are added. If the walk continues, with probability $1 - p_w$, the scientist decides where to step, i.e. which co-author to add. The author looks to all and only the people they have collaborated with previously, and chooses one of them randomly, weighted according to how many times they have co-authored in the past.

This newly added co-author becomes the ‘walker’ and the process continues. With probability p_w the walk stops, and if the walk continues, the new walker’s collaboration history probabilistically determines who gets added to the collaboration. If a new co-author is added, there is again a probability the walk stops, or that this third author walks to one of their connections on the network and passes the baton to a yet a new walker, and so on. (Though there is an order in which authors are added, this does not affect anything in the model, e.g. the person who joins first temporally is not given first author position.) This might seem like an odd way to determine sets of co-authors, but, intuitively, it just abstracts away from all the various reasons to co-author with a person — having similar interests, being from the same institution, etc. — and captures the sum of all those reasons with the observation that a person is more likely to co-author with someone they have more frequently co-authored in the past.

Once the set of co-authors is determined (i.e., the walk stops), the paper is then categorized according the discipline of the majority of its authors. So, if there are two physicists and one biologist, the paper is labeled a physics paper. Similarly, the discipline of the authors is determined by the disciplines of the papers they have written in the past.

Growth: After this, with probability p_n a new scientist enters. If they do, they automatically write a paper with a co-author, who is chosen uniformly at random from those in the network and who can then add additional co-authors through the biased random walk process described above. The automatic assignment of one co-author guarantees that new authors are integrated into the network. Otherwise, they would not be able to walk anywhere, and no one could walk to them to add them as a co-author.

Landscape change: The creation of these collaborations affects the evolution of disciplines. As collaborations develop, this increases the weight of the links between the co-authors, indicating their ties are stronger. Some scientists will be more closely tied to each other than to the rest of the network, generating clusters of closely connected individuals.

Each round there is a probability, p_d, to check for a *split event*, where some part of the network has become clustered enough, and separate enough from the rest, to call it an independent discipline. Sun et al. (2013) use a community detection algorithm based on *modularity*. Roughly, this algorithm looks at the extent to which there is higher connectivity within a part of the network than would be expected if connections in the network were randomly generated.[1] They choose a discipline at random, consider all possible ways of splitting the discipline in two, and, if the modularity after a split is higher than before a split, make the split with highest modularity. If there is a split event, the smaller of the two clusters is considered to be a new discipline. The labels of existing papers in the community are then updated – if a majority of a paper's authors are in the new community, it is categorized as part of that new discipline – as well as author disciplines according to the new paper labels.

Likewise, what previously looked like two clusters might come closer together as people start collaborating across the clusters. So, each round there is also a chance,

[1] More specifically, modularity measures compare the number of edges within a part of the network to the expected number in a null model. In this algorithm, the null model is generated by shuffling the edges in the network generated in the simulation, while ensuring the degree sequence is the same (Newman, 2006).

again p_d, to check for a *merge event*. In this case, two disciplines with at least one common author are randomly selected and merged if this increases modularity of the network as a whole. If there is a merge, the smaller cluster is now considered part of the discipline of the larger cluster and paper labels and author disciplines are updated accordingly. Thus, the process of collaboration affects the structure of the research community, and the evolution of disciplines within it.[2]

4 Incorporating Inequities

While we take the basic model from Sun et al. (2013), we are interested in different questions. As mentioned, we are motivated by the observation that fields associated with marginalized groups tend to be devalued and the hypothesis that the social dynamics of collaboration are an important part of this story. So, we incorporate into the model ways that social identity can affect aspects of collaboration.[3]

First, data shows that there is often an unequal division of credit within collaborations. Women and members of minority groups are less likely to hold prestigious first and last author positions, and tend to put in more work in a lab while being less likely to be given any authorship at all (see, e.g. West et al., 2013; Feldon et al., 2017). In other words, they tend to get less credit from the products of their joint work. We know something about the short- or medium-term consequences of this unequal division of credit within collaborations. For instance, it can affect who scientists

[2] Sun et al. (2013) verified that this model captured important features of the real evolution of scientific disciplines, such as the distribution of collaboration size and number of papers per scientist, and we checked that our results were qualitatively similar as well.

[3] Our code can be found at https://osf.io/6uafr/?view_only=fc972f9fd5864abbb17887177ca06d42, with further information at https://github.com/kekoawong/scienceDynamicsModel.

choose to collaborate with, as they try to avoid unfair collaborations. Thus, inequity can affect the collaboration network within a single discipline, ultimately leading to segregation or clustering along social identity lines (Ferber and Teiman, 1980; McDowell and Smith, 1992; Rubin and O'Connor, 2018). This, however, leaves open questions of the long-term consequences of collaboration inequity for the shape of the scientific community and our valuation of knowledge produced within whole disciplines.

Another aspect of inequity is the Matthew effect, where the rich get richer (Rossiter, 1993). In this context, there are two ways that past credit accumulated for one's work can affect the future credit one expects to receive. First, past credit affects the probability that a person gets added onto a collaboration; high reputation from past credit makes it more likely to be asked to join projects in the future, thus increasing the amount of work for which a person gets credit in the future (Chakraborty and Chandra, 2016). Second, past credit also affects how much credit is generated by each new paper that author produces. Papers by well-known people are more likely to be widely read and highly cited (Petersen et al., 2014).

We incorporate these three factors — collaboration inequity and two aspects of the Matthew effect — into the modeling framework developed by Sun et al. (2013) to show how they can affect the overall shape of the scientific community over time. We build in each feature one by one, yielding three models. In addition, we incorporate 'retirement' into the models, where a scientist stops collaborating. (The node stays in the network but is no longer an active part of the network.) Unlike Sun et al. (2013), we track reputation of scientists, so including this retirement mechanism avoids distorting our view of how reputation can accumulate to a person over the lifetime of their career. To keep things simple, scientists retire after 1,000 time steps, though section 5 will discuss how we might make this more complicated.

Model 1: We start with a model incorporating collaboration inequity. We introduce 'types' into the model, which do not affect anything except the credit an author receives for a paper. We assume that a type 1 agent gets 1 unit of credit per paper they collaborate on, where a type 2 agent gets 2 units. Therefore, being type 1 represents being a member of a marginalized group and receiving less credit for your work than a member of a dominant group, consistent with empirical evidence regarding how credit is often distributed.

Model 2: The next model additionally incorporates reputation, where reputation is a function of a person's total accumulated credit. There are diminishing returns of credit on reputation – e.g., 10 new citations are worth more to someone just starting out versus someone at the top of their field – captured in the model by reputation equalling the square root of an author's total credit accumulated. Model 2 then includes everything from model 1 plus the aspect of the Matthew effect where past credit increases chances to be added to a project; the probability to choose someone as a co-author now depends both on past co-authoring and author reputation.[4]

Model 3: The final model allows past reputation to feed into future credit generated per paper. Since, again, there are diminishing returns to accumulation of credit, we say that the reputation of the set of authors is found by summing up the credit accumulated by all authors in the collaboration, then taking the square root of that. Model 3 includes everything from model 2 plus the assumption that papers generate an amount of credit, c_p, according to total reputation of the collaborators involved. In this case, type 1 agents

[4]Formally, author i's reputation (r_i) is a function of their credit accumulated from all their papers (c_i): $r_i = \sqrt{c_i}$. We multiply linking probabilities in model 1 by $log_e(r_i)$ and normalize so that the values sum to 1.

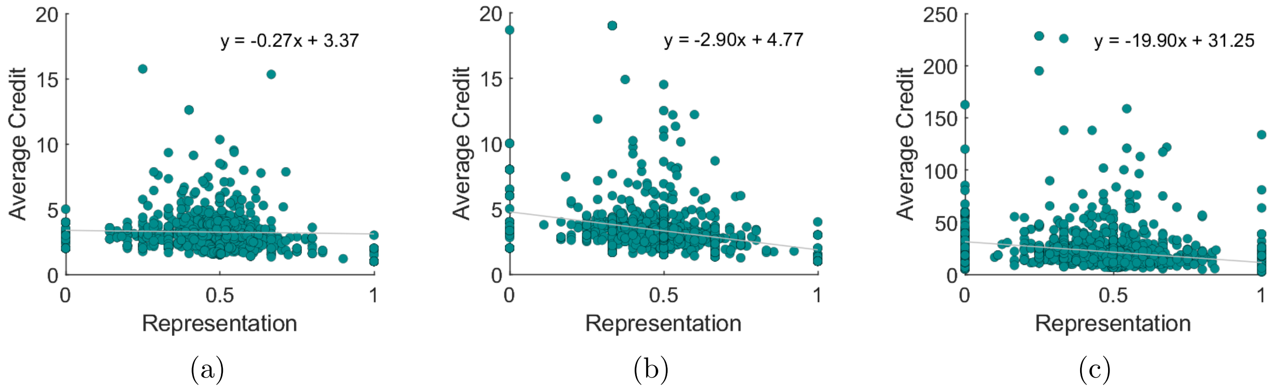

Figure 1: Average credit per author vs. representation of marginalized group in each discipline for (a) model 1, (b) model 2, and (c) model 3.

receive $1 \times c_p$ and type 2 receive $2 \times c_p$ for the paper.

4.1 Contagion Results

The percent marginalized researchers in a field predicts the average credit per paper coming out in that field. Figure 1 shows scatter-plots of all the disciplines, for all runs of the simulation, according to the representation of the marginalized group (on the x-axis, with higher numbers indicating a higher proportion of marginalized researchers) and the average credit each author in that discipline accumulates (on the y-axis).[5]

Figure 1a shows that the more marginalized researchers there are, the less credit accumulated by the average person in that field. In particular, the slope of a linear regression is negative but small in model 1.[6] That the slope is negative is unsurprising. This is essentially built into the model, as each paper produced by a marginalized

[5]10 simulations were run for 10,000 time-steps for each model.

[6]The linear regressions in figure 1 are not intended as best fit lines, but only to capture the negative relationship between credit and a field's association with a marginalized group.

researcher is worth less — they might manage to accumulate as much total credit as a member of the dominant group, but they would have to publish twice as many papers. However, the contagion of disrespect is not simply an observation that fields associated with marginalized groups are seen as less good, rather it is that they are increasingly dismissed as unimportant to the generation of scientific knowledge. Looking to models 2 and 3, the way this collaboration inequity interacts with the way reputation functions in these collaboration dynamics can start to give us a better picture of how a contagion of disrespect might arise.

As seen in figure 1b, in model 2, the slope of the linear regression is more negative, meaning that researchers in fields associated with marginalized groups tend to be seen as even less productive of scientific knowledge than researchers in other fields. The slope is even more negative in figure 1c; in model 3, authors generate less credit still in fields associated with marginalized groups. The scale is different for this model versus the other two – because the credit per paper varies based on the authors – making very specific comparisons of model 3 with models 1 and 2 somewhat complicated.

However, we *can* see from model 3 that incorporating reputation building gives rise to something we can call a contagion of disrespect. When reputation has no effect, as in model 1, results produced by disciplines associated with marginalized groups are devalued, but only due to pre-existing inequities, rather than anything to do with the collaboration dynamics that affect the evolution of disciplines. Then, when reputation is incorporated, as in model 2, the collaboration dynamics begin to come into play in terms of the possibility of people preferentially collaborating with those who happen to have slightly higher reputation. However, those people only have higher reputation if they by chance write more papers, and the number of papers any one person writes during their career is limited. There is no mechanism by which the difference between authors can substantially increase over time, or by which these high reputation authors can increase the reputation of their co-authors, who are likely to be in their field.

In model 3, the reputation building aspect of the Matthew effect provides exactly that kind of mechanism, where the reputation of individuals, and as a side-effect, the reputation of disciplines, can increase over time. This reputation building benefits the dominant group more – credit feeds into future credit for all scholars, but members of the dominant group have more credit to feed into that process at the start.[7] In conjunction with collaboration inequity according to social identity, we can then see the emergence of a contagion of disrespect, where new results by authors in fields associated with marginalized groups generate less and less relative credit, or are seen as less and less important to scientific knowledge.

For each of the three models, we can also plot a histogram of the credit produced within the disciplines (figure 2). This reveals that there is a higher skew in the distribution of credit over fields in model 3 (figure 2c) versus model 2 (figure 2b) versus 1 (figure 2a). In other words, credit, relative to the total amount of credit produced, is less evenly distributed across fields as we include additional reputational effects, consistent with the above description of increasing dismissal of certain fields. As is likely

[7] Though figures are not included here due to space considerations, we can also consider the distribution of credit accumulated to each individual across disciplines. In model 1, the distribution of credit across members of the dominant group is roughly similar to the distribution of credit across members of the marginalized group, except that the scale is twice that of the scale for the marginalized group members (since they receive twice the credit per paper). In model 2, even accounting for this difference in scale, there are more marginalized group members at the low end of the distribution, accumulating very little credit over their career, but there are roughly similar numbers at the high end of the distribution. In model 3, again accounting for the difference in scale, there are both fewer members of the dominant group at the low end of the distribution and more at the top end when compared with members of the marginalized group.

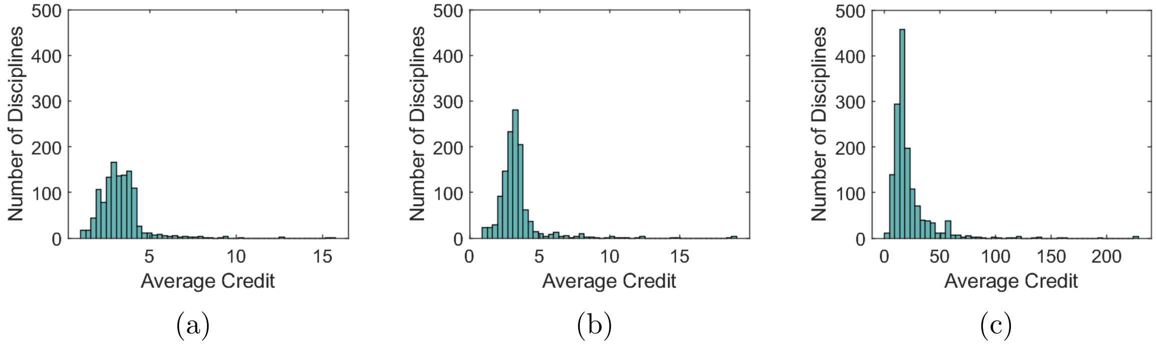

Figure 2: Histogram of average credit produced across all disciplines for (a) model 1, (b) model 2, and (c) model 3.

unsurprising, though it is not shown in figure 2, fields associated with marginalized groups tend to be on the lower end of the distribution, i.e they are the ones that are being increasingly dismissed.

5 Discussion

We conclude that a contagion of disrespect can emerge based on observed features of collaboration dynamics. Of course, there are several factors left out of this analysis. For instance, when we incorporated aspects of the Matthew effect, we did not include the observation that a less famous person often gets a lower share of the credit for the co-authored paper. We also did not include homophily, where people tend to link more often with others of their same social identity group, or any attempt at avoiding unequal collaborations (Rubin and O'Connor, 2018); on the more segregated networks these processes produce, the affects of inequality and the Matthew effect would likely be amplified. As mentioned, we also included a very simplified exit dynamic where people retired after a certain number of rounds. It might be more plausible to assume that people not accumulating a certain amount of credit leave the field after not securing permanent employment. Including this might allow us to say something more about why certain fields, like the field of Child Study, diminish and eventually disappear from the scientific landscape altogether.

It is important to emphasize that our explanation is not incompatible with there being a range of biases. In our model, fields are dismissed due to low average credit generated per author or per paper, but fields can also be dismissed because people have preconceived notions about their worth. Something like this is arguably the case with indigenous forestry and ecology. In reality, these phenomena (and others, like institutional barriers) are not going to be cleanly separable, and likely act in conjunction. So, we ought not to conclude that we can explain devaluation of fields only by appeal to collaboration dynamics.

However, it is important to know the variety of factors working against disciplines associated with marginalized researchers. This knowledge affects how we think about our connections to a history of dismissal of certain kinds of knowledge and it impacts how we might address current devaluation. For example, there have been recent pushes to address some instances of devaluation by recognizing the legitimacy of various ways of knowing. While potentially ameliorative, these measures will not necessarily put productive fields of research on the equal footing they deserve. In the long term, we will need to address collaboration inequity as well.

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