INSIGHTS

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Toward a more scientific science

Climb atop shoulders and wait for funerals. That, suggested Newton and then Planck, is how science advances (more or less). We've come far since then, but many notions about how people and practices, policies, and resources influence the course of science are still more rooted in traditions and intuitions than in evidence. We can and must do better, lest we resign ourselves to "intuition-based policy" when making decisions and investments aimed at driving scientific progress. *Science* invited experts to highlight key aspects of the scientific enterprise that are steadily yielding to empirical investigation— and to explain how Newton and Planck got it right (and Einstein got it wrong). —**Brad Wible**

One superstar funeral at a time

By **Pierre Azoulay**[1,2] *and* **Joshua Graff-Zivin**[2,3]

Max Planck wrote that "A new scientific truth does not triumph by convincing its opponents and making them see the light, but rather because its opponents eventually die." Despite all of their contributions to science, might "superstar" scientists also use their central position to stymie the arrival of new ideas? To shed empiri- cal light on this issue, we turned to a ghoulish natural experiment, assessing impacts of the premature deaths of 452 eminent life sci- entists (median age at death = 61 years). We implemented a proce- dure (drawing on automated analysis of keywords in publications) to delineate the boundaries of the intellectual neighborhoods in which eminent scientists worked and conceptualized the prema- ture deaths as shocks to the structure of these neighborhoods. We found that after the deaths, the stars' expansive rosters of collabo- rators tend to drastically reduce their scientific output (1), whereas noncollaborators increase their output in the deceased stars' field

Corrected 28 February 2019. See full text.

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– Isaac Newton

recent literature—work commonly sampled by search engines (4)—are not particularly likely to be hits. Second, hit papers mix highly typical and highly novel ideas and do so roughly according to a 90/10 ratio (5). Such papers referencing highly familiar knowledge—literature that historically has been cited together much more frequently than expected by chance—while at the same time citing papers that have rarely been co-cited before are at least twice as likely to be hits in their field than the average paper. Novelty is prized in science but becomes especially influential when paired with familiar, conventional thought. Sampling the literature also depends on team work. Team-authored papers are more likely to draw on work in the 5-year-old hotspot and to insert novel combinations into familiar knowledge domains than papers by solo authors (3, 5). Such insights take us closer to uncovering approaches for searching for and recombining yesterday's ideas into tomorrow's acclaimed discoveries (6, 7).

On shoulders of giants

By **Heidi Williams**[1,2]

Isaac Newton famously noted, "If I have seen further than others, it is by standing on the shoulders of giants," highlighting the idea that many scientific discoveries enable future discoveries. Yet although the scientific community makes tremendous investments aimed at finding new discoveries, much less attention focuses on improving access to past discoveries—efforts that could help us, like Newton, to "see further than others." Although the idea that past discoveries may enable future discoveries is quite intuitive, measures of and mechanisms for such so-called "cumulative innovation" have traditionally proven elusive to pin down empirically. Two recent empirical studies have made progress. First, biological resource centers—"living libraries" of biological materials, such as cell lines—appear to increase follow-on research by more than 50% (8). Second, limitations on access to sequenced human genes— used by the private firm Celera during the "race" to sequence the human genome—reduced subsequent research and development on those genes by around 30% (9). These studies share two key features. Both generated novel linkages between records of scientific discoveries (such as sequenced human genes) and measures of cumulative innovation (such as gene-based medical diagnostic tests). In addition, both isolated natural experiments, in which otherwise similar scientific discoveries were "treated" by different institutions and policies—akin to a randomized controlled trial— lending credibility to a causal and policy-relevant interpretation of the results. Taken together, these findings suggest that the institutions and policies that govern how past discoveries are accessed can have dramatic effects on cumulative innovation.

(2). Moreover, these additional contributions are disproportionately likely to be highly cited and are more likely to be authored by scientists who were not previously active in the superstar's field before his or her death. This suggests that intellectual, social, and resource barriers impede entry into new subfields, with outsiders only entering subfields that offer a less hostile landscape for the support and acceptance of "foreign" ideas. Although the contributions of stars to the advancement of science are unassailable, our results suggest that once in control of the commanding heights of their fields, star scientists tend to hold on to their exalted position a bit too long.

Novelty and hotspots

By **Brian Uzzi**[4,5,6] and **Dashun Wang**[4,5,6]

Recent research on nearly 27 million scientific papers since 1950, and more than 5 million U.S. patents since 1970, shows that how scientists sample the ever-expanding literature is critical to making breakthroughs, irrespective of discipline. First, papers or patents that cite literature of a certain age range (mean of about 5 years, with a high variance) are roughly twice as likely to be a hit (in the top 5% of citations) than a field's average paper (3). By contrast, the 75% of papers and patents that combine knowledge from outside this "hotspot," referencing the most popular or most

A crowded frontier

By **James A. Evans**[7]

Science is a complex system in which rapid circulation of advances has resulted in scientists crowding the same frontier of accumulated knowledge, constrained to imagine the same combinations of ideas and methods that they might use to unlock discoveries, rather than exploring more broadly. Applying computational tools to massive corpora of digitized scientific texts and databases of experimental results, recent research has advanced our ability to trace the dynamic frontier of collective attention and explore how we might accelerate discovery, identifying possibilities missed by

the crowd and potentially uninferrable by any particular scientist. For example, nearly all combinations of scientific components in a given year's papers, most of them highly redundant, can be predicted by random walks across the network traced by papers published in the prior year (*10*). Algorithms can identify hypotheses unimagined and paths untaken, not necessarily because they lack scientific promise but because scientists are channeled away by shared institutional realities, such as the incentive to build on work familiar to one's audience (and reviewers) (*11*, *12*). This incentive, combined with the difficulty to publish results from failed experiments, draws scientists to the same congested areas of common knowledge, pitted with unmarked failures doomed to repetition, and so dramatically slows the pace of collective discovery (*13*). These patterns have been exploited to generate algorithms unhampered by professional pressures for publication and promotion, which more efficiently survey the space of scientific possibilities. These findings highlight the importance of supporting diverse approaches and independence in research, and of building institutions that log failures as well as successes in order to accelerate collective advancement.

Retraction and reputation

By **Ginger Zhe Jin**[2,8,9] *and* **Susan Feng Lu**[9]

Retractions of scientific articles are increasingly common. Driven by community policing and self-reported errors, retractions could reflect innocent mistakes or intentional misconduct. Although a retracted article always suffers severe losses in citations, it was not until recently that literature documented broader reputational consequences of retraction for authors. Although authors of retracted papers commonly have "clean" works that were not retracted at any time and were published before their other work was retracted, the research community may take retraction as a signal of the authors' quality and cast doubt on those prior works. Comparing such prior papers' citations after the retraction, to control papers of similar citation history, reveals a 5 to 10% citation decline for the prior works, but only if the retraction is not self-reported (*14*) or involves intentional misconduct (*15*). Reputation loss also depends on author standing. Comparing author's standing across retraction events shows that eminent scientists (as measured with cumulative citation and funding before retraction) are more harshly penalized in the citation of their prior works, if the retraction involves misconduct (*16*). However, within scientific teams, the blameworthy party is often nonobvious. In these cases, the most eminent team members appear to escape largely unscathed, whereas less eminent coauthors experience substantial citation declines, especially when teamed with eminent authors (*17*). This result holds for both absolute eminence and relative eminence within the team. In short, reputational effects for individual scientists can be substantial after retraction occurs but depend on the nature of the retraction and the author's standing.

Science across the ages

By **Benjamin F. Jones**[4]

Einstein said, "A person who has not made his great contribution to science before the age of 30 will never do so." But was Einstein right? The relationship between age and scientific productivity matters not only for assessing one's own potential but also for science institutions deciding whom to hire, promote, and fund.

Yet although many observers have echoed Einstein's view, empirical studies have rejected it with remarkable consistency. Great achievements come at many ages and typically peak between the mid-30s and mid-40s (*18*). This finding holds across science, engineering, and social science fields, including for Nobel Prize–winning contributions. It also holds among celebrated inventors (*19*) and successful technology entrepreneurs (*20*). Recent research also emphasizes a dynamic view: Nobel Prize–winning contributions and great inventions came 8 years later in life at the end of the 20th century than at the beginning (*19*). This shift is due to a sharp decline in great contributions at very young ages. This shift also appears among more ordinary careers, for which the age at first invention is rising 0.6 years per decade (*21*). The increasing depth of scientific knowledge can make subsequent generations take longer to reach the research frontier (*19*, *21*). Additionally, although an individual's best works typically come in close succession, such "hot streaks" can happen, with equal probability, anywhere in the sequence of an individual's body of work (*22*). Overall, although entry to science is an increasingly long road, and scientists may write fewer papers later in life, opportunity endures: The next hot streak could be just around the corner.

Modeling and mapping

By **Katy Börner**[10,11]

Studies of science, technology, and innovation (STI) have traditionally focused on analyzing historical data. Yet increasingly, decision-makers wish to understand likely impacts of today's, for example, hires, resource allocations, and legal decisions on the unfolding of future STI scenarios. Thus, computational models are increasingly used to explore aspects of the STI system itself (*23*), with hundreds of ways to visualize and communicate the structure and dynamics of STI (*24–26*). For example, models have been used to experiment and validate alternative approaches for funding science that might

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be less subject to biases, inconsistencies, and "old-boy" network effects associated with standard peer review and reduce the time, energy, and effort spent on writing and reviewing research proposals and the overhead required to organize the review process. Under the Fund-Rank model (27), each year all eligible scholars receive an equal portion of funding but are then required to anonymously donate a certain fraction of their funding to peers. This agent-based model was validated by using large-scale citation data (37 million articles and 770 million citations), presuming that scholars would distribute funding similarly to how they distribute citations, namely to those peers who do valuable, high-quality research. Other work models the return on investment for university-supported information technology (IT) resources on winning external funding and publishing papers (28); Sankey diagrams visualize correlations of IT usage, external funding, and publications and support IT strategic decision-making. Ultimately, such predictive models help develop and refine hypotheses, explore the impact of different parameters, capture causal relationships, and pick desirable futures.

Randomized insights

By **Karim R. Lakhani**[2,12,13], **Kevin J. Boudreau**[2,14], **Eva C. Guinan**[13,15,16]

Although there is a growing body of research that describes various aspects of the scientific enterprise, it is largely observational, which limits which questions can be investigated and what causal inferences can be drawn. We have worked closely with scientists to layer large-scale randomized field experiments onto preexisting university research processes in order to generate causal insights (29, 30). Little is known as to how scientific collaborations form. We hypothesized that finding collaborators is a costly "search" that shapes the number and type of collaborations (31). At a research symposium related to an institutional funding opportunity, attended by 400 scientists, we randomly enabled face-to-face interactions during 90-minute scientific idea–sharing sessions. Among teams that applied for funding, the probability of collaboration increased by 75% for the treated scientists compared with controls (same idea-sharing but not face to face). However, the collaborations occurred only within the same scientific domains. This highlights the role of scientific meetings and structured information sharing for increasing collaboration (as opposed to waiting for serendipity) and the barriers to collaboration across disciplines. To understand the role of cognitive biases in peer review, we randomly assigned 150 proposals for institutional research funding to 142 faculty reviewers (~15 applications per reviewer; 2130 evaluations total) (32). Controlling for the quality of the proposals, reviewers gave poorer scores to proposals that were closer to their own field of expertise (based on automated text analysis of the applications and of reviewers' publications). More novel proposals (based on text analysis, relative to all publications in the PubMed database) also received poorer scores. This highlights the importance of constructing appropriate review panels and establishing procedures that can eliminate bias against novelty.

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Science

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