Science of science

Santo Fortunato[1,2,*], Carl T. Bergstrom[3], Katy Börner[4,2], James A. Evans[5], Dirk Helbing[6], Staša Milojević[1], Alexander M. Petersen[7], Filippo Radicchi[1], Roberta Sinatra[8,9,10], Brian Uzzi[11,12], Alessandro Vespignani[10,13,14], Ludo Waltman[15], Dashun Wang[11,12], Albert-László Barabási[10,16,8,*]

[1] *Center for Complex Networks and Systems Research, School of Informatics and Computing, Indiana University, Bloomington, USA*
[2] *Indiana University Network Science Institute (IUNI), Indiana University, Bloomington, USA*
[3] *Department of Biology University of Washington Seattle, WA USA*
[4] *Cyberinfrastructure for Network Science Center, School of Informatics and Computing, Indiana University, Bloomington, USA*
[5] *Department of Sociology, University of Chicago, Chicago IL 60637, USA*
[6] *Computational Social Science, ETH Zurich, Zurich, Switzerland*
[7] *Ernest and Julio Gallo Management Program, School of Engineering, University of California, Merced, California 95343, USA*
[8] *Center for Network Science, Central European University, Budapest 1052, Hungary.*
[9] *Department of Mathematics, Central European University, Budapest 1051, Hungary.*
[10] *Institute for Network Science, Northeastern University, Boston MA 02115, USA*
[11] *Kellogg School of Management, Northwestern University, Evanston, IL 60208, USA*
[12] *Northwestern Institute on Complex Systems (NICO), Northwestern University, Evanston, IL 60208, USA*
[13] *Laboratory for the Modeling of Biological and Sociotechnical Systems, Northeastern University, Boston MA 02115, USA*
[14] *ISI Foundation, Turin 10133, Italy*
[15] *Centre for Science and Technology Studies, Leiden University, Leiden, Netherlands*
[16] *Center for Cancer Systems Biology, Dana-Farber Cancer Institute, Boston MA 02115, USA*

*Correspondence to: santo@indiana.edu, barabasi@gmail.com

Abstract

Identifying fundamental drivers of science and developing predictive models to capture its evolution are instrumental for the design of policies that can improve the scientific enterprise, from enhanced career paths for scientists, to improved performance evaluation for organizations hosting research, to discovery of novel effective funding vehicles, and even identification of promising regions along the scientific frontier. Science of science uses large-scale data on the production of science to search for universal as well as domain-specific patterns. Here we review recent developments in this transdisciplinary field.

The deluge of digital data on scholarly output offers unprecedented opportunities to explore patterns characterizing the structure and evolution of science. Science of Science (SciSci) places the practice of science itself under the microscope, attaining a new quantitative understanding of the genesis of scientific discovery, creativity, and practice, and developing tools and policies aimed at accelerating scientific progress.

The emergence of SciSci has been driven by two key factors. The first is data availability. In addition to the proprietary Web of Science, the first historic citation index (*1*), today multiple data sources are available (Scopus, PubMed, Google Scholar, Microsoft Academic, USPTO, etc.), some freely accessible, covering millions of data points pertaining to scientists and their output, capturing research from all over the world and all branches of science. Second, SciSci has benefited from an influx of, and collaborations among, natural, computational and social scientists who have developed new Big Data-based capabilities and enabled critical tests of generative models that aim to capture the unfolding of science, its institutions and workforce.

One distinctive characteristic of the emerging SciSci is how it breaks down disciplinary boundaries. SciSci integrates findings and theories from multiple disciplines and utilizes a wide range of data and methods. From scientometrics it takes the idea of measuring science from large-scale data sources, from the sociology of science it adopts theoretical concepts and social processes, and from innovation studies pathways through which science contributes to invention and economic change. SciSci relies on a broad collection of quantitative methods, from descriptive statistics and data visualization to advanced econometric methods, network science approaches and machine learning algorithms, mathematical analysis and computer simulation, including agent-based modeling.

The value proposition of SciSci hinges on the hypothesis that with a deeper understanding of the factors behind successful science, we can enhance the prospects of science as a whole to more effectively address societal problems.

Networks of scientists, institutions and ideas

Contemporary science is a dynamical system of undertakings driven by complex interactions between social structures, knowledge representations and the natural world. Scientific knowledge is constituted by concepts and relations embodied in research papers, books, patents, software, and other scholarly artifacts, organized into scientific disciplines and broader fields. These social, conceptual and material elements are connected through formal and informal flows of information, ideas, research practices, tools and samples. Science can thus be described as a complex, self-organizing and constantly evolving multi-scale network.

Early studies discovered an exponential growth in the volume of scientific literature (*2*), a trend that continues with an average doubling period of 15 years (Fig. 1). Yet, it would be naïve to equate the growth of the scientific literature with the growth of scientific ideas. Changes in the publishing world, both technological and economic, have led to increasing efficiency in the production of publications. Moreover, new publications in science tend to cluster in discrete areas of knowledge (*3*). Large-scale text analysis, using phrases extracted from titles and abstracts to measure the cognitive extent of the scientific literature, have found that the conceptual territory of science expands linearly with time. In other words, while the number of publications grows exponentially, the space of ideas expand only linearly, a much slower process (Fig. 1) (*4*).

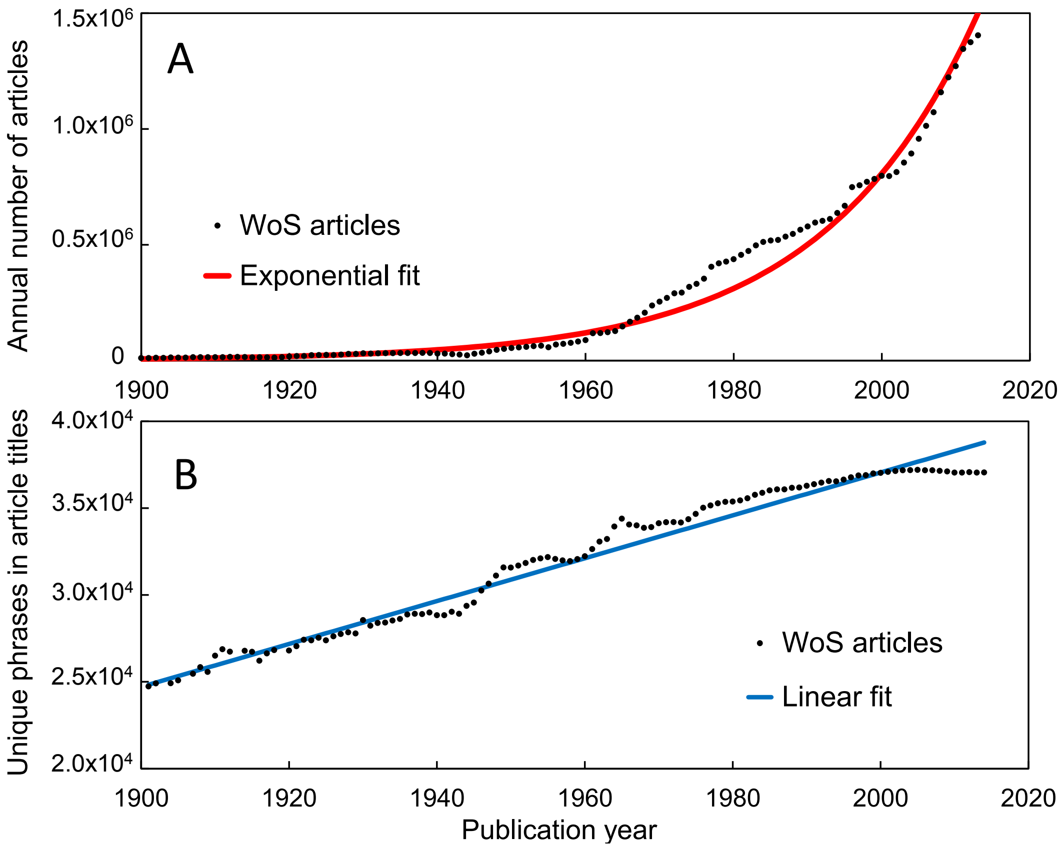

Figure 1. **Growth of science**. (A) Annual production of scientific articles indexed in the Web of Science (WoS) database. (B) Growth of ideas covered by articles indexed in the WoS. This was determined by counting unique title phrases (concepts) in a fixed number of articles (*4*).

Frequently occurring words and phrases in article titles and abstracts propagate via citation networks, punctuated by bursts corresponding to the emergence of new paradigms (*5*). By applying network science methods to citation networks, researchers are able to identify communities comprised by subsets of publications that frequently cite one another (*6*). These communities often correspond to groups of authors holding a common position regarding specific issues (*7*) or working on the same specialized subtopics (*8*). Recent work focusing on biomedical science has illustrated how growth of the literature reinforces these communities (*9*). As new papers are published, associations (hyperedges) between scientists, chemicals, diseases and methods ("things", which are the nodes of the network) are added. Most new links fall between things only one or two steps away from each other, implying that when scientists choose new topics, they prefer things directly related to their current expertise, or that of their collaborators. This densification suggests that the existing structure of science may constrain what will be studied in the future.

Densification at the boundaries of science is also a signal of transdisciplinary exploration, fusion, and innovation. A lifecycle analysis of eight fields (*10*) shows that successful fields undergo a process of knowledge and social unification that leads to a giant connected component in the collaboration network, corresponding to a sizeable group of regular coauthors. A model in which scientists choose their collaborators via random walks on the coauthorship network successfully reproduces author productivity, the number of authors per discipline and the interdisciplinarity of papers and authors (*11*).

Problem selection

How do scientists decide which research problems to work on? Sociologists of science have long hypothesized that these choices are shaped by an ongoing tension between productive tradition and risky innovation (*12, 13*). Scientists who adhere to a research tradition in their domain often appear productive by publishing a steady stream of contributions advancing a focused research agenda. But a focused agenda may limit a researcher's ability to sense and seize opportunities for staking out new ideas required to grow the field's knowledge. For example, a case study focusing on biomedical scientists choosing novel chemicals and chemical relationships shows that as fields mature researchers tend to focus increasingly on established knowledge (*3*). Although an innovative publication tends to result in higher impact than a conservative one, high-risk innovation strategies are rare, as the additional reward does not compensate for the risk of failure to publish at all. Scientific awards and accolades appear to function as primary incentives to resist conservative tendencies and encourage betting on exploration and surprise (*3*). Despite the many factors shaping what scientists work on next, macroscopic patterns that govern changes in research interests along scientific careers follow highly reproducible patterns, documenting a high degree of regularity underlying scientific research and individual careers (*14*).

Scientists' choice of research problems affects primarily their individual careers and the careers of those reliant on them. Scientists' collective choices, however, determine the direction of scientific discovery as a whole (Fig. 2). Conservative strategies (*15*) serve individual careers well, but are less effective for science as a whole. Such strategies are amplified by the file drawer problem (*16*): negative results, at odds with established hypotheses, are rarely published, leading to a systemic bias in published research and the canonization of weak and sometimes false facts (*17*). Indeed, more risky hypotheses may have been tested by generations of scientists, but only those successful enough to result in publications are known to us. One way to alleviate this conservative trap is to urge funding agencies to proactively sponsor risky projects that test truly unexplored hypotheses and take on special interest groups advocating for particular diseases. Measurements show that the allocation of biomedical resources in the U.S. is more strongly correlated to previous allocations and research than to the actual burden of diseases (*18*), highlighting a systemic misalignment between biomedical needs and resources. This misalignment casts doubts on the degree to which funding agencies, often run by scientists embedded in established paradigms, are likely to influence the evolution of science without introducing additional oversight, incentives and feedback.

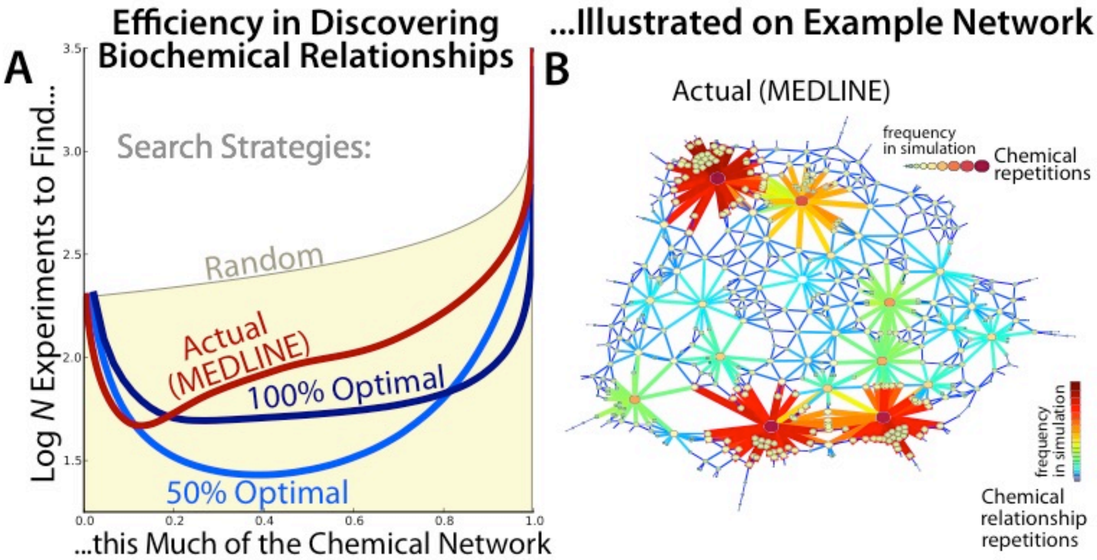

Figure 2. **Choosing experiments to accelerate collective discovery**. The average efficiency rate for global strategies to discover new, publishable chemical relationships, estimated from all MEDLINE-indexed articles published in 2010. This model does not take into account differences in the difficulty or expense of particular experiments. (A) The efficiency of a global scientific strategy is expressed by the average number of experiments performed (vertical axis) relative to the number of new, published biochemical relationships (horizontal axis), which correspond to new connections in the published network of biochemicals co-occurring in MEDLINE-indexed articles. Compared strategies include randomly choosing pairs of biochemicals, the global strategy inferred from all scientists publishing MEDLINE articles, and optimal strategies for discovering 50% and 100% of the network. Lower values on the vertical axis indicate higher efficiency strategies. The actual strategy used by science as a system is not optimal for discovery. (B) The actual, estimated search process illustrated on a hypothetical network of chemical relationships, averaged from 500 simulated runs of that strategy. The strategy swarms around a few "important", highly connected chemicals, whereas optimal strategies are much more even and less likely to "follow the crowd" in their search across the space of scientific possibilities. After Ref. (*15*).

Novelty

Analyses of publications and patents consistently reveal that rare combinations in scientific discoveries and inventions tend to result in outcomes that garner higher citation rates (*3*). Interdisciplinary research is an emblematic recombinant process (*19*), hence the successful combination of previously disconnected ideas and resources that is fundamental to interdisciplinary research often violates expectations and leads to novel ideas with high impact (*20*). Nevertheless, evidence from grant applications shows that, when faced with new ideas, expert evaluators systematically give lower scores to truly novel (*21-23*) or interdisciplinary (*24*) research proposals.

The highest-impact science is primarily grounded in conventional combinations of prior work, yet it simultaneously features unusual combinations (*25, 26*). Papers of this type are twice as likely to receive high citations (*26*). In other words, a balanced mixture of new and established elements is the safest path towards successful reception of scientific advance.

Career dynamics

Individual academic careers unfold in the context of a vast market for knowledge production and consumption (*27*). Consequently, scientific careers have been examined not only in terms of individual incentives and marginal productivity (i.e., relative gain versus effort) (*28*), but also institutional incentives (*29, 30*) and competition (*31*). This requires combining large repositories of high-resolution individual, geographic, and temporal metadata (*32*), to construct representations of career trajectories that can be analyzed from different perspectives. For example, one study finds that funding schemes tolerant of early failure, which reward long-term success are more likely to generate high impact publications than grants subject to short review cycles (*30*). Interacting systems with competing timescales are a classic problem in complex systems science. The multi-faceted nature of science is motivation for generative models that highlight unintended consequences arising form science policy. For example, models of career growth show that non-tenure (short-term) contracts are responsible for productivity fluctuations, which often result in a sudden career death (*28*).

Gender inequality in science remains prevalent and problematic (*33*). Women have less publications (*34-36*), collaborators (*37*), funding (*38*) and are penalized in hiring decisions when compared to equally qualified men (*39*). The causes of this gap are still unclear. Intrinsic differences in productivity rates and career length can explain the differences in collaboration patterns (*37*) and hiring rates (*34*) between male and female scientists. On the other hand, experimental evidence shows that biases against women occur at very early career stages. When gender was randomly assigned among the CVs of a pool of applicants, the hiring committee systematically penalized female candidates (*39*). Most studies so far have focused on relatively small samples. Improvements in compiling large scale datasets of scientific careers, which leverage information from different sources, e.g. publication records, grant applications and awards, will help us gain deeper insight into the causes of inequality, identify causes, and motivate models that can inform policy solutions.

Scientists' mobility is another important factor offering diverse career opportunities. Most mobility have focused on quantifying the brain drain and gain of a country or a region (*40-42*), especially following policy changes. Research on individual mobility and its career effect remains scant, however, primarily due to the difficulty of obtaining longitudinal information about the movements of many scientists, accounting for the reasons underlying mobility decisions. Scientists who left their country of origin outperformed scientists that did not relocate, according to the impact factor of journals that published scientist's work, a finding that may be rooted in a selection bias that offers better scientists with better career opportunities (*43*). Moreover, scientists tend to move between institutions of similar prestige (*44*). Nevertheless, when examining changes in impact associated with each move, quantified by citations, no systematic increase or decrease was found, not even when scientists moved to an institution of significantly higher or lower rank (*45*). In other words, it is not the institution that creates the impact, it is the individual researchers that make an institution.

Another potentially important career factor is reputation, and the dilemma it poses for manuscript review, proposal evaluation and promotion decisions. The reputation of paper authors, measured by the total citations to their previous output, markedly boosts the number of citations collected by that paper in the first years after publication (*46*). Following this initial phase, however, impact depends on the reception of the work by the scientific community. This finding, along with Ref. (*45*), suggests that, for productive scientific careers, reputation is less of a critical driver for success than talent, hard work and relevance. This is at odds with artistic careers, where future success is guaranteed once the artists land in the top artistic venues.

A policy-relevant question is whether creativity and innovation depend on age or career stage. Decades of research on outstanding researchers and innovators concluded that major breakthroughs take place relatively early in a career, with a median age of 35 (*47*). In contrast, recent work shows that this well-documented propensity of early-career discoveries is fully explained by productivity, which is high in the early stages of a scientist's career and drops later (*48*). In other words, there are no age patterns in innovation: a scholar's most cited paper can be any of his or her papers, independently of the age or career stage when it is published (Fig. 3). A stochastic model of impact evolution also indicates that breakthroughs result from a combination between the ability of a scientist and the luck to pick a problem with a high potential (*48*).

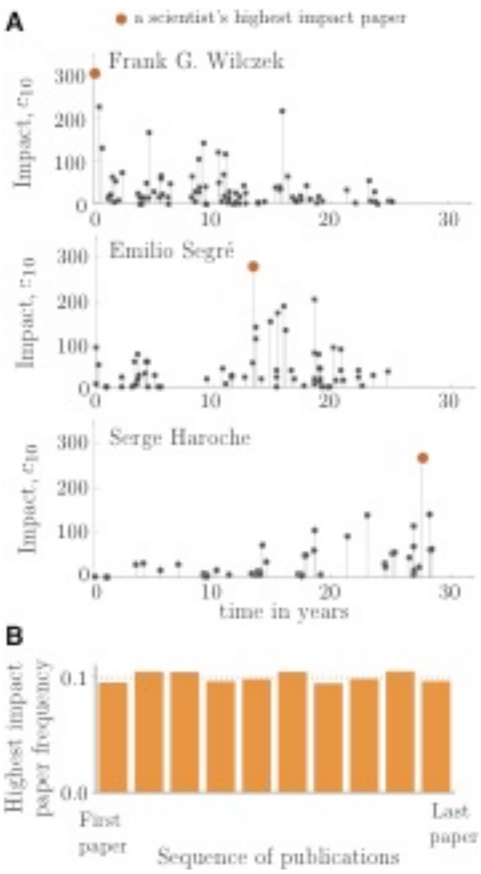

Figure 3. Impact in scientific careers. (A) Publication record of three Nobel Laureates in physics. The horizontal axis indicates the number of years after a Laureate's first publication and each circle corresponds to a research paper, the height of the circle representing the paper's impact, quantified by c_{10}, number of citations after 10 years.

The highest impact paper of a Laureate is denoted with an orange circle. These Nobel Laureates published their highest impact work at different stages of their career. (B) Histogram of the occurrence of the highest impact paper in a scientist's sequence of publications, calculated for 10,000 scientists. The flatness of the histogram indicates that the highest impact work can be, with the same probability, anywhere in the sequence of papers published by a scientist – it could be the first publication, could appear in her mid-career or could be the last publication (*random impact rule*) (*48*).

Team science

During past decades there has been increased reliance on teamwork, representing a fundamental shift in the way science is done. A study of the authorship of 19.9 million research articles and 2.1 million patents reveals a nearly universal shift toward teams in all branches of science (*49*). For example, in 1955 science and engineering teams authored about the same number of papers as single authors. Yet by 2013, the fraction of team-authored papers increased to 90 percent (*50*) (Fig. 4).

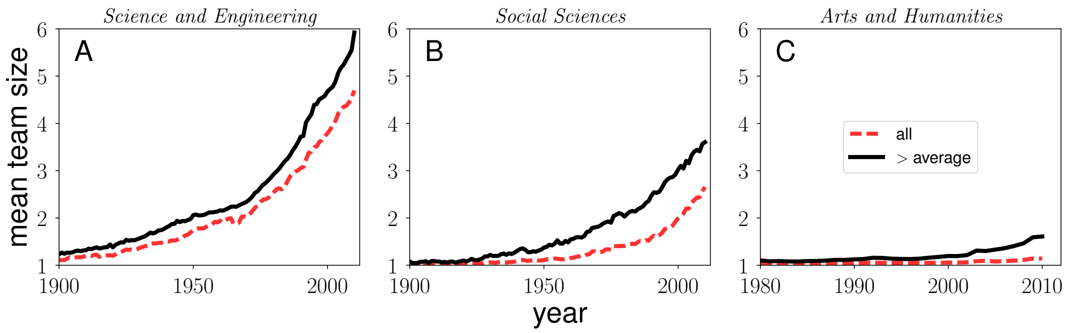

Figure 4. **Size and impact of teams**. Mean team size has been steadily growing over the last century. The dashed line refers to the mean number of coauthors over all papers, the black one considers just those papers receiving more citations than the average for the field. Black curves are systematically above the dashed ones, meaning that high impact work is more likely to be produced by large teams than by small ones. Each panel corresponds to one of the three main disciplinary groups of papers indexed in the Web of Science: Science and Engineering (A); Social Sciences (B); Arts and Humanities (C).

Today a team-authored paper in science and engineering is 6.3 times more likely to receive 1,000 citations or more than a solo-authored paper, a difference that cannot be explained by self-citations (*49, 51*). One possible reason is a team's ability to come up with more novel combinations of ideas (*26*), or the production of resources that are later used by others (e. g., genomics). Indeed, measurements show that teams are 38% more likely than solo authors to insert novel combinations into familiar knowledge domains, supporting the premise that teams can bring together different specialties, effectively combining knowledge that prompts scientific breakthroughs. Having more collaborations means greater visibility through a larger number of coauthors, who will likely introduce the work to their networks, an enhanced impact that may partially compensate for the fact that in a team setting credit must be shared with many colleagues (*28*).

Despite the fact that work from large teams receives, on average, more citations, researchers working alone or in small teams may actually cover a wider cognitive extent than large teams (*4*). Consequently, large teams tend to focus on a subset of well-established problems, but small teams appear to push the frontiers of science into new areas that may receive subsequent exploration by larger teams. Thus it may be important to fund and foster teams of all sizes, in order to temper the bureaucratization of science (*27*).

Teams are also growing in size, increasing by an average of 17% per decade (*49, 52*), a trend underlying a fundamental change in team compositions. Scientific teams include both small stable "core" teams and large dynamically changing extended teams (*53*). The increasing team size in most fields is driven by faster expansion of extended teams, which begin as small core teams, but subsequently attract new members through a process of cumulative advantage anchored by productivity. Size is a crucial determinant of team survival strategies: small teams survive longer if they maintain a stable core, but larger teams persist longer if they manifest a mechanism for membership turnover (*54*).

As science has accelerated and grown increasingly complex, the instruments required to expand the frontier of knowledge have increased in scale and precision. The tools of the trade become unaffordable to most individual investigators, but also to most institutions. Collaboration was a critical solution, pooling resources to scientific advantage. The Large Hadron Collider, the world's largest and most powerful particle collider at CERN, would have been unthinkable without collaboration, requiring over 10,000 scientists and engineers from over 100 countries. There is, however, a tradeoff with increasing size that affects the value and risk associated with 'big science' (*2*). While it may be possible to solve larger problems, the burden of reproducibility may require duplicating initial efforts, which may not be practically or economically feasible.

Collaborators can have a big effect on scientific careers. According to recent studies (*55, 56*) scientists who lose their star collaborators experience a significant drop in their productivity, especially if the lost collaborator was a regular coauthor. Publications involving extremely strong collaborators gain on average 17% more citations, pointing to the value of career partnership drawing on the benefits of risk and reward sharing (*57*).

Given the increasing number of authors on the average research paper, who should and does gain the most credit? The canonical theory of credit (mis)allocation in science is the Matthew effect (*58*), where scientists of higher statuses involved in joint work receive outsized credit for their contributions. Properly allocating individual credit for a collaborative work is difficult because we cannot easily distinguish individual contributions (*59*). By inspecting the co-citation patterns of the coauthors' publications, we can determine the fraction of credit the community assigns to each coauthor in a publication (*60*).

Citation dynamics

Scholarly citation remains the dominant measurable unit of credit in science. Given the reliance of most impact metrics on citations (*61-64*), the dynamics of citation accumulation have been scrutinized by generations of scholars. From foundational work by Price (*65*), we know that the distribution of citations for scientific papers is highly skewed: many papers are never cited, but seminal papers can accumulate 10,000 or more citations. This uneven citation distribution is a robust, emergent property of the dynamics of science, and holds when papers are grouped by institution (*66*). If the number of citations of a paper is divided by the average number of citations collected by papers in the same discipline and year, the distribution of the resulting score is essentially indistinguishable for all disciplines (*67, 68*) (Fig. 5A). This means that we can compare the impact of papers published in different disciplines by looking at their relative citation values. For example, a paper in mathematics collecting 100 citations represents a higher disciplinary impact than a paper in microbiology with 300 citations.

The tail of the citation distribution, capturing the number of high impact papers, sheds light on the mechanisms that drive the accumulation of citations. Recent analyses show that it follows a power law (*69-71*). Power-law tails can be generated via a *cumulative advantage* process (*72*), known as *preferential attachment* in network science (*73*), suggesting that the probability to cite a paper grows with the number of citations that it has already collected. Such a model can be augmented with other characteristic features of citation dynamics, like the obsolescence of knowledge, decreasing the citation probability with the age of the paper (*74-77*), and a fitness parameter, unique to each paper, capturing the appeal of the work to the scientific community (*75, 76*). Only a tiny fraction of papers deviate from the pattern described by such a model – some of which are called *sleeping beauties*, as they receive very little attention for decades after publication, until they suddenly receive a burst of attention and citations (*78, 79*).

The generative mechanisms described above can be used to predict the citation dynamics of individual papers. One predictive model (*75*) assumes that the citation probability of a paper depends on the number of previous citations, an obsolescence factor and a fitness parameter (Fig. 5B, 5C). For a given paper one can estimate the three model parameters by fitting the model to the initial portion of the citation history of the paper, and the long-term impact of the work can be extrapolated (*75*). Other studies have identified predictors of the citation impact of individual papers (*80*), like journal impact factor (*70*). It has been suggested that the future h-index (*81*) of a scientist can be accurately predicted (*82*), although the predictive power is reduced when accounting for the scientists' career stage and the cumulative non-decreasing nature of the h-index (*83*). Eliminating inconsistencies in the use of quantitative evaluation metrics in science is crucial, and highlights the importance of understanding the generating mechanisms behind commonly used statistics.

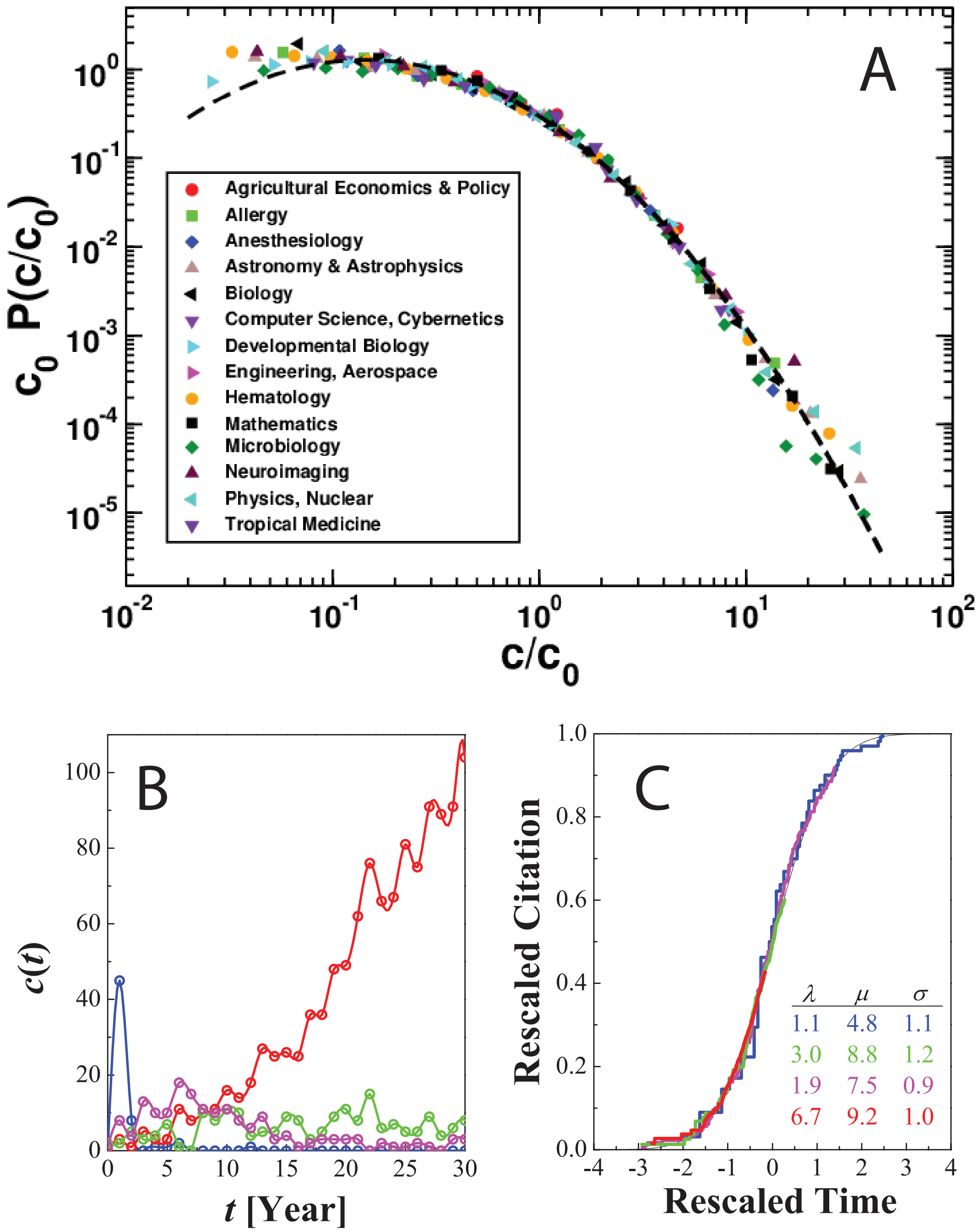

Figure 5. **Universality in citation dynamics**. (A) The citation distributions of papers published in the same discipline and year lie on the same curve for most disciplines, if the raw number of cites *c* of each paper is divided by the average number of cites c_0 over all papers in that discipline and year. The dashed line is a lognormal fit. After Ref. (*67*). (B) Citation history of four papers published in Physical Review in 1964, selected for their distinct dynamics, displaying a 'jump-decay' pattern (blue); delayed peak (magenta); attracting a constant number of citation over time (green), or acquiring an increasing number of citations each year (red). (C) Citations of an individual paper are determined by three parameters: fitness λ_i, immediacy μ_i, and longevity σ_i. By rescaling the citation history of each paper in (B) by the appropriate (λ, μ, σ) parameters, the four papers collapse onto a single universal function, which is the same for all disciplines. After Ref. (*75*).

Outlook

Despite the discovery of universals across science, substantial disciplinary differences in culture, habits, and preferences make some cross-domain insights difficult to appreciate within particular fields and associated policies challenging to implement. The questions, data and skills required by each discipline suggest that we may gain further insights from domain-specific SciSci studies that model and predict opportunities adapted to the needs of each field. For young scientists, the results of SciSci offer actionable insights about past patterns, helping guide future inquiry within their disciplines (Box 1).

The contribution of SciSci is a detailed understanding of the relational structure between scientists, institutions and ideas, a crucial starting point that facilitates the identification of fundamental generating processes. Together, these data-driven efforts complement contributions from related research domains such as the economics (*29*) and sociology of science (*58, 84*). Causal estimation is a prime example, in which econometric matching techniques demand and leverage comprehensive data sources in the effort to simulate counterfactual scenarios (*30, 42*). Assessing causality is one of the most needed future developments in SciSci: many studies reveal strong associations between structure and outcomes but the extent to which a specific structure "causes" an outcome remains unexplored. Engaging in tighter partnerships with experimentalists, SciSci will be able to better identify associations discovered from models and large scale data that have causal force to enrich their policy relevance. But experimenting on science may be the biggest challenge SciSci is yet to face. Indeed, running randomized, controlled trials that can alter outcomes of individuals or institutions of science, which are mostly supported by tax dollars, is

Box 1. Lessons from Science of Science.

1. **Innovation and tradition**: Left bare, truly innovative and highly interdisciplinary ideas may not fulfill maximum scientific impact. To enhance their impact, place novel ideas in the context of established knowledge. Ref. 26.
2. **Persistence**: You are never too old to make a discovery, as long as you stay productive. Ref. 48.
3. **Collaboration:** Research is shifting to teams, so engaging in collaboration is beneficial. Small teams may be more innovative, but big teams have more impact. Ref. 4.
4. **Credit**: The quantity of effort and the ideas you provide to an article does not determine the credit you receive for a discovery. Most credit will go to the coauthors with the most consistent track record in the domain of the publication Ref. 60.
5. **Peer review:** The publication and impact of each paper is influenced by the reputation of its authors. Double-blind review could mitigate the effect of reputation bias in assessing a discovery. Ref. 46.
6. **Funding:** While review panels acknowledge innovation, they tend to discount it. Funding agencies should ask reviewers to assess innovation, not only expected success. Ref. 24.

bound to criticisms and pushbacks (*85*). Hence we expect quasi-experimental approaches to prevail in SciSci investigations in near future.

Most SciSci research focuses on publications as primary data sources, implying that insights and findings are limited to ideas successful enough to merit publication in the first place. Yet most scientific attempts fail, sometimes spectacularly. Given that scientists fail more often than they succeed, knowing when, why and how an idea fails is essential in our attempts to understand and improve science. Such studies could provide meaningful guidance towards the reproducibility crisis and help us account for the file drawer problem. They could also substantially further our understanding of human imagination by revealing the total pipeline of creative activity.

Science often behaves like an economic system with a one-dimensional "currency" of citation counts. The one-dimensional performance measure of citation counts creates a hierarchical system, in which the "rich-gets-richer" dynamics suppress the spread of new ideas, particularly those from junior scientists and those who do not fit within the paradigms supported by specific fields. Science can be improved by broadening the number and range of performance indicators. The development of alternative metrics of web (*86*) and social media (*87*) activity and of societal (*88*) and economic (*89*) impact is critical in this regard. Other measurable dimensions include the information (e.g., data) that scientists share with competitors (*90*), the help they offer to their peers (*91*) and their reliability as reviewers of their peers' works (*92*). But with a profusion of metrics, more work is needed to understand what each of them does and does not capture, to ensure a meaningful interpretation and avoid misuse. SciSci makes an essential contribution by providing models that offer a deeper understanding of the mechanisms that govern performance indicators in science.

The integration of citation-based metrics with alternative indicators will promote pluralism and enable new dimensions of productive specialization, in which scientists can be successful in different ways. The system of science is an ecosystem, which requires not publications as output, but also communicators and teachers, visionaries and detail-oriented experts. We need individuals who can ask novel field-altering questions, as well as those who can answer them. It would benefit science if curiosity, creativity and intellectual exchange, particularly regarding the societal implications and applications of science and technology, are better appreciated and incentivized in the future. A more pluralistic approach could reduce duplicity and make science flourish for society.

An issue that SciSci can seek to improve is the allocation of science funding. The current peer review system is subject to biases and inconsistencies (*93*). Several alternatives have been proposed, such as the random distribution of funding (*94*), person-directed funding that does not involve proposal preparation and review (*30*), opening the proposal review process to the entire online population (*95*) or removing human reviewers altogether by allocating funds equally, randomly, or through a performance measure (*96*), or through scientist crowd-funding (*97*).

To predict future scientific practice and advance, a critical area of future research for SciSci concerns the integration of machine learning and artificial intelligence in a way that involves machines and minds distinctly working together. Such mind+machine partnerships have improved evidence-based decision-making in a wide range of health, economic, social, legal and business problems (*98-100*) How can science be improved with mind+machine partnerships and what arrangements are most productive? These questions promise to help us understand the science of the future. They prompt reexamination of answers about how teams and networks form; how students can most successfully be trained and mentored; how the rate of breakthroughs might be sped up by reimagining the division of labor between the wisdom and intuition of individual scientists, and the ability of machines to ingest and process massive amounts of “mashed up” physical, biological and social data. These studies will need to incorporate the interdisciplinary approach of SciSci to simultaneously explore the social, computational, and material aspects of mind+machine partnerships and their spillovers into teamwork, training, and discovery.

REFERENCES

1. E. Garfield, Citation indexes for science: A new dimension in documentation through association of ideas. *Science* **122**, 108-111 (1955).
2. D. J. d. S. Price, *Little science, big science*. (Columbia University Press, New York, 1963).
3. J. G. Foster, A. Rzhetsky, J. A. Evans, Tradition and innovation in scientists’ research strategies. *American Sociological Review* **80**, 875-908 (2015).
4. S. Milojević, Quantifying the cognitive extent of science. *Journal of Informetrics* **9**, 962-973 (2015).
5. T. Kuhn, M. Perc, D. Helbing, Inheritance patterns in citation networks reveal scientific memes. *Physical Review X* **4**, 041036 (2014).
6. R. Klavans, K. W. Boyack, Which Type of Citation Analysis Generates the Most Accurate Taxonomy of Scientific and Technical Knowledge? *Journal of the Association for Information Science and Technology* **68**, 984-998 (2016).
7. U. Shwed, P. S. Bearman, The temporal structure of scientific consensus formation. *American Sociological Review* **75**, 817-840 (2010).
8. J. Bruggeman, V. A. Traag, J. Uitermark, Detecting communities through network data. *American Sociological Review* **77**, 1050-1063 (2010).
9. F. Shi, J. G. Foster, J. A. Evans, Weaving the fabric of science: Dynamic network models of science’s unfolding structure. *Social Networks* **43**, 73-85 (2015).
10. L. M. A. Bettencourt, D. I. Kaiser, J. Kaur, Scientific discovery and topological transitions in collaboration networks. *Journal of Informetrics* **3**, 210-221 (2009).
11. X. Sun, J. Kaur, S. Milojević, A. Flammini, F. Menczer, Social dynamics of science. *Scientific Reports* **3**, 1069 (2013).
12. T. S. Kuhn, *The essential tension: Selected studies in scientific tradition and change*. (University of Chicago Press, Chicago, 1977).
13. P. Bourdieu, The specificity of the scientific field and the social conditions of the progress of reasons. *Social Science Information* **14**, 19-47 (1975).

14. T. Jia, D. Wang, B. K. Szymanski, Quantifying patterns of research-interest evolution. *Nature Human Behaviour* **1**, 0078 (2017).
15. A. Rzhetsky, J. G. Foster, I. T. Foster, J. A. Evans, Choosing experiments to accelerate collective discovery. *Proceedings of the National Academy of Sciences* **112**, 14569-14574 (2015).
16. R. Rosenthal, The file drawer problem and tolerance for null results. *Psychological Bulletin* **86**, 638 (1979).
17. S. B. Nissen, T. Magidson, K. Gross, C. T. Bergstrom, Publication bias and the canonization of false facts. *Elife* **5**, e21451 (2016).
18. L. Yao, Y. Li, S. Ghosh, J. A. Evans, A. Rzhetsky, Health ROI as a measure of misalignment of biomedical needs and resources. *Nature Biotechnology* **33**, 807-811 (2015).
19. C. S. Wagner *et al.*, Approaches to understanding and measuring interdisciplinary scientific research (IDR): A review of the literature. *Journal of Informetrics* **5**, 14-26 (2011).
20. V. Larivière, S. Haustein, K. Börner, Long-distance interdisciplinarity leads to higher scientific impact. *PLoS ONE* **10**, e0122565 (2015).
21. K. J. Boudreau, E. C. Guinan, K. R. Lakhani, C. Riedl, Looking across and looking beyond the knowledge frontier: Intellectual distance, novelty, and resource allocation in science. *Management Science*, (2016).
22. E. Leahey, J. Moody, Sociological innovation through subfield integration. *Social Currents* **1**, 228-256 (2014).
23. A. Yegros-Yegros, I. Rafols, P. D'Este, Does Interdisciplinary Research Lead to Higher Citation Impact? The Different Effect of Proximal and Distal Interdisciplinarity. *PLoS ONE* **10**, e0135095 (2015).
24. L. Bromham, R. Dinnage, X. Hua, Interdisciplinary research has consistently lower funding success. *Nature* **534**, 684-687 (2016).
25. D. Kim, D. B. Cerigo, H. Jeong, H. Youn, Technological novelty profile and inventions future impact. *EPJ Data Science* **5**, 1 (2016).
26. B. Uzzi, S. Mukherjee, M. Stringer, B. F. Jones, Atypical combinations and scientific impact. *Science* **342**, 468-472 (2013).
27. J. P. Walsh, Y.-N. Lee, The bureaucratization of science. *Research Policy* **44**, 1584-1600 (2015).
28. A. M. Petersen, M. Riccaboni, H. E. Stenley, F. Pammolli, Persistence and uncertainty in the academic career. *Proceedings of the National Academy of Sciences* **109**, 5213-5218 (2012).
29. P. E. Stephan, *How economics shapes science*. (Harvard University Press, Cambridge, MA, 2012).
30. P. Azoulay, J. G. Zivin, G. Manso, Incentives and creativity: Evidence from the academic life sciences. *RAND Journal of Economics* **42**, 527-554 (2011).
31. R. B. Freeman, E. Weinstein, E. Marincola, J. Rosenbaum, F. Solomon, Competition and careers in biosciences. *Science* **294**, 2293-2294 (2001).
32. J. A. Evans, J. G. Foster, Metaknowledge. *Science* **331**, 721-725 (2011).
33. V. N. Larivière, Chaoqun Ni; Gingras, Yves; Cronin, Blaise; Sugimoto, Cassidy R. , Bibliometrics: Global gender disparities in science. *Nature* **504**, 211-213 (2013).
34. S. F. Way, D. B. Larremore, A. Clauset, in *World Wide Web Conference (WWW)*. (ACM, Montreal, 2016), pp. 1169-1179.

35. J. Duch *et al.*, The possible role of resource requirements and academic career-choice risk on gender differences in publication rate and impact. *PLoS ONE* **7**, e51332 (2012).
36. J. D. West, J. Jacquet, M. M. King, S. J. Correll, C. T. Bergstrom, The role of gender in scholarly authorship. *PLoS ONE* **8**, e66212 (2013).
37. X. H. T. Zeng *et al.*, Differences in collaboration patterns across discipline, career stage, and gender. *PLoS Biology* **14**, e1002573 (2016).
38. T. J. Ley, B. H. Hamilton, The gender gap in NIH grant applications. *Science* **322**, 1472-1474 (2008).
39. C. A. Moss-Racusin, J. F. Dovidio, V. L. Brescoll, M. J. Graham, J. Handelsman, Science faculty's subtle gender biases favor male students. *Proceeding of the National Academy of Science* **109**, 16474-16479 (2012).
40. R. Van Noorden, Science on the move. *Nature* **490**, 326 (2012).
41. B. A. Weinberg, Developing science: Scientific performance and brain drains in the developing world. *Journal of Developmental Economics* **95**, 95-104 (2011).
42. O. A. Doria Arrieta, F. Pammoll, A. M. Petersen, Quantifying the negative impact of brain drain on the integration of European science. *Science Advances* **3**, e1602232 (2017).
43. C. Franzoni, G. Scellato, P. Stephan, The mover's advantage: The superior performance of migrant scientists. *Economics Letters* **122**, 89-93 (2014).
44. A. Clauset, S. Arbesman, D. B. Larremore, Systematic inequality and hierarchy in faculty hiring networks. *Science Advances* **1**, e1400005 (2015).
45. P. Deville *et al.*, Career on the move: Geography, stratification, and scientific impact. *Scientific Reports* **4**, (2014).
46. A. M. Petersen *et al.*, Reputation and impact in academic careers. *Proceedings of the National Academy of Sciences* **111**, 15316-15321 (2014).
47. D. K. Simonton, Creative productivity: A predictive and explanatory model of career trajectories and landmarks. *Psychological Review* **104**, 66-89 (1997).
48. R. Sinatra, D. Wang, P. Deville, C. Song, A.-L. Barabási, Quantifying the evolution of individual scientific impact. *Science* **354**, (2016).
49. S. Wuchty, B. F. Jones, B. Uzzi, The increasing dominance of teams in production of knowledge. *Science* **316**, 1036-1039 (2007).
50. N. J. Cooke, M. L. Hilton, Eds., *Enhancing the effectiveness of team science*, (The National Academies Press, Washington, D.C., 2015).
51. V. Larivière, Y. Gingras, C. R. Sugimoto, A. Tsou, Team size matters: Collaboration and scientific impact since 1900. *Journal of the Association for Information Science and Technology* **66**, 1323-1332 (2015).
52. B. F. Jones, The burden of knowledge and the "death of the renaissance man"�: Is innovation getting harder? *The Review of Economic Studies* **76**, 283--317 (2009).
53. S. Milojević, Principles of scientific research team formation and evolution. *Proceedings of the National Academy of Sciences (PNAS)* **111**, 3984-3989 (2014).
54. G. Palla, A.-L. Barabási, T. Vicsek, Quantifying social group evolution. *Nature* **446**, 664--667 (2007).

55. G. J. Borjas, K. B. Doran, Which peers matter? The relative impacts of collaborators, colleagues, and competitors. *Review of Economics and Statistics* **97**, 1104--1117 (2015).
56. P. Azoulay, J. G. Zivin, J. Wang, Superstar Extinction. *Quarterly Journal of Economics* **125**, 549--589 (2010).
57. A. M. Petersen, Quantifying the impact of weak, strong, and super ties in scientific careers. *Proceedings of the National Academy of Sciences* **112**, E4671--E4680 (2015).
58. R. K. Merton, The Matthew effect in science. *Science* **159**, 56-63 (1968).
59. L. Allen, J. Scott, A. Brand, M. Hlava, M. Altman, Credit where credit is due. *Nature* **508**, 312--313 (2014).
60. H.-W. Shen, A.-L. Barabási, Collective credit allocation in science. *Proceedings of the National Academy of Sciences* **111**, 12325--12330 (2014).
61. L. Waltman, A review of the literature on citation impact indicators. *Journal of Informetrics* **10**, 365-391 (2016).
62. J. E. Hirsch, An index to quantify an individual's scientific research output. *PNAS* **102**, 16569-16572 (2005).
63. H. F. Moed, *Citation analysis in research evaluation*. (Springer, Dordrecht, 2010).
64. E. Garfield, Citation Analysis as a Tool in Journal Evaluation. *Science* **178**, 471-479 (1972).
65. D. J. d. S. Price, Networks of scientific papers. *Science* **149**, 510-515 (1965).
66. Q. Zhang, N. Perra, B. Gonçalves, F. Ciulla, A. Vespignani, Characterizing scientific production and consumption in Physics. *Scientific Reports* **3**, 1640 (2013).
67. F. Radicchi, S. Fortunato, C. Castellano, Universality of citation distributions: Toward an objective measure of scientific impact. *PNAS* **105**, 17268-17272 (2008).
68. L. Waltman, N. J. van Eck, A. F. J. van Raan, Universality of citation distributions revisited. *Journal of the Association for Information Science and Technology* **63**, 72-77 (2012).
69. M. Golosovsky, S. Solomon, Runaway events dominate the heavy tail of citation distributions. *The European Physical Journal Special Topics* **205**, 303-311 (2012).
70. C. Stegehuis, N. Litvak, L. Waltman, Predicting the long-term citation impact of recent publications. *Journal of Informetrics* **9**, 642-657 (2015).
71. M. Thelwall, The discretised lognormal and hooked power law distributions for complete citation data: Best options for modelling and regression. *Journal of Informetrics* **10**, 336-346 (2016).
72. D. J. d. S. Price, A general theory of bibliometric and other cumulative advantage processes. *Journal of the American Society for Information Science* **27**, 292-306 (1976).
73. A.-L. Barabási, R. Albert, Emergence of scaling in random networks. *Science* **286**, 509-512 (1999).
74. P. D. B. Parolo *et al.*, Attention decay in science. *Journal of Informetrics* **9**, 734-745 (2015).

75. D. Wang, C. Song, A.-L. Barabási, Quantifying long-term scientific impact. *Science* **342**, 127-132 (2013).
76. Y.-H. Eom, S. Fortunato, Characterizing and modeling citation dynamics. *PLoS ONE* **6**, e24926 (2011).
77. M. Golosovsky, S. Solomon, Stochastic dynamical model of a growing citation network based on a self-exciting point process. *Physical Review Letters* **109**, 098701 (2012).
78. A. F. J. van Raan, Sleeping Beauties in Science. *Scientometrics* **59**, 467-472 (2004).
79. Q. Ke, E. Ferrara, F. Radicchi, A. Flammini, Defining and identifying sleeping beauties in science. *Proceedings of the National Academy of Sciences USA* **112**, 7426–7431 (2015).
80. I. Tahamtan, A. S. Afshar, K. Ahamdzadeh, Factors affecting number of citations: a comprehensive review of the literature. *Scientometrics* **107**, 1195-1225 (2016).
81. J. E. Hirsch, Does the h index have predictive power? *Proceedings of the National Academy of Sciences* **104**, 19193-19198 (2007).
82. D. E. Acuna, S. Allesina, K. P. Kording, Future impact: Predicting scientific success. *Nature* **489**, 201-202 (2012).
83. O. Penner, R. K. Pan, A. M. Petersen, K. Kaski, S. Fortunato, On the predictability of future impact in science. *Scientific Reports* **3**, 3052 (2013).
84. J. R. Cole, H. Zuckerman, in *The Idea of Social Structure: Papers in Honor of Robert K. Merton,* L. A. Coser, Ed. (Harcourt Brace Jovanovich, New York, 1975), pp. 139-174.
85. P. Azoulay, Research efficiency: turn the scientific methods on ourselves. *Nature* **484**, 31-32 (2012).
86. M. Thelwall, K. Kousha, Web indicators for research evaluation. Part 1: Citations and links to academic articles from the Web. *El Profesional de la Información* **24**, 587-606 (2015).
87. M. Thelwall, K. Kousha, Web indicators for research evaluation. Part 2: Social media metrics. *El Profesional de la Información* **24**, 607-620 (2015).
88. L. Bornmann, What is societal impact of research and how can it be assessed? A literature survey. *Advances in Information Science* **64**, 217-233 (2013).
89. M. Ahmadpoor, B. F. Jones, The dual frontier: Patented inventions and prior scientific advance. *Science* **357**, 583-587 (2017).
90. C. Haeussler, L. Jiang, J. Thursby, M. Thursby, Specific and general information sharing among competing academic researchers. *Research Policy* **43**, 465-475 (2014).
91. A. Oettl, Sociology: Honour the helpful. *Nature* **489**, 496-497 (2012).
92. S. Ravindran, in *Careers*. (AAAS, Science, 2016).
93. S. Wessely, Peer review of grant applications: what do we know? *The Lancet* **352**, 301-305 (1998).
94. N. Geard, J. Noble, paper presented at the 3rd World Congress on Social Simulation, 2010.
95. Editor, Calm in a crisis. *Nature* **468**, 1002 (2010).
96. R. Roy, Funding science: The real defects of peer review and an alternative to it. *Science, Technology, and Human Values* **10**, 73 (1985).

97. J. Bollen, D. Crandall, D. Junk, Y. Ding, K. Börner, An efficient system to fund science: from proposal review to peer-to-peer distributions. *Scientometrics* **110**, 521-528 (2017).
98. M. S. Kohn *et al.*, 2014. *Yearbook of Medical Informatics* **9**, 154-162.
99. J. Kleinberg, H. Lakkaraju, J. Leskovec, J. Ludwig, S. Mullainathan, "Human Decisions and Machine Predictions," (National Bureau of Economic Research, 2017).
100. B. Liu, R. Govindan, B. Uzzi, Do Emotions Expressed Online Correlate with Actual Changes in Decision-Making?: The Case of Stock Day Traders. *PLoS ONE* **11**, e0144945 (2016).

ACKNOWLEDGMENTS

This work was supported by Air Force Office of Scientific Research grants FA9550-15-1-0077 (A.-L. B, R. S. and A. V.), FA9550-15-1-0364 (A.-L. B. and R. S.), FA9550-15-1-0162 (J. E. and D. W.) and FA9550-17-1-0089 (D. W.); National Science Foundation grants NCSE 1538763, EAGER1566393, NCN CP Supplement 1553044 (K. B.), and SBE1158803 (J. E.); National Institutes of Health awards P01 AG039347, U01CA198934 (K. B.) and IIS-0910664 (B. U.); Army Research Office grant W911NF-15-1-0577 and Northwestern University Institute on Complex Systems (B. U.); DARPA's Big Mechanism program grant 14145043 (J. E.) and the John Templeton Foundation's grant to the Metaknowledge Network (J. E.); The European Commission, H2020 Framework program, Grant 641191 CIMPLEX (R. S., A.-L. B.). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of our funders.