The Science of Science

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Part 2: The Science of Collaboration

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In 2015, Marco Drago was a postdoctoral researcher at the Albert Einstein Institute in Hannover, Germany, working on the Laser Interferometer Gravitational-Wave Observatory (LIGO) experiment. The project's goal was to detect gravitational waves—ripples in the fabric of space and time caused by the collision of two black holes. Drago spent most of his time overseeing one of four data "pipelines"—automated computer systems which scoured the raw data coming from the LIGO detectors for unusual signals. Just before lunch on September 14, 2015, while on the phone with a colleague, he received an automated email alert notifying him that the 4 km-long tunnels housing sensitive laser beams in ultrahigh vacuum, had just vibrated. Such an event was not uncommon, but as Drago clicked open the email, he quickly realized this one was different. The event it reported was *huge* by LIGO's standards. While the vibration was less than a trillionth of an inch, that was more than double the size of a typical event. It was so large, in fact, that Drago instantly dismissed it. It seemed too good to be true.

It took another five months to officially confirm the truth behind the September 14th event. As announced on February 12, 2016, the event registered by the automated email had been the real deal. That tiny signal told us that about 1.3 billion years ago, across the universe, two black holes collided, forming a new black hole that was sixty-two times as heavy as our sun. Their collision radiated a hundred times more energy than all the stars in the universe combined, generating gravitational waves that rippled in every direction. Weakening as they travelled through space at the speed of light, the waves finally reached Earth on that quiet September morning in 2015, shaking the detectors by about a thousandth of the diameter of a proton. That vibration validated the prediction of Albert Einstein's general theory of relativity, becoming, according to some, the "discovery of the 21st century."

While Drago was the lucky person who saw the signal first, it wasn't really *his* discovery. An international team of scientists spent over 40 years building the experiment, and when the paper [1] reporting the detection of gravitational waves was finally published, it listed over 1,000 authors from all over the world. There were the physicists who dreamed up the project and calculated its feasibility, the engineers who designed the tunnels, and the administrative staff who oversaw the day to day operations. At $1.1 billion, LIGO is still the largest and most ambitious project ever funded by the U.S. National Science Foundation (NSF).

By contrast, when the Prussian Academy of Science first heard about what would be deemed the "discovery of the twentieth century" in November of 1915, it had a single author, Albert Einstein. Occurring exactly one hundred years apart, these two discoveries reveal an important way that science has changed over the past century. We imagine science as a solitary endeavor, picturing Einstein, Darwin, and Hawking on solo journeys, inching toward that "Eureka!" moment. Yet today, most science is carried out by teams [2, 3]. Indeed, 90 percent of all science and engineering publications are written by multiple authors. These can be two-person teams, such as Watson and Crick, who unveiled the structure of DNA, but many important discoveries are made through large-scale collaborations, like those pursued at CERN, the Manhattan Project, or Project Apollo. Scientific teams have produced breakthroughs that could not have been achieved by lone investigators. And such large-scale team projects often have an enormous impact, not just on science, but on the economy and society. Take for example the Human Genome Project. It not only jump started the genomic revolution; its direct expenditures of about $3.8 billion also generated $796 billion in economic growth and created 310,000 jobs [4]. However, these kinds of massive collaborations also introduce a new set of unique challenges for scientists, from team communication to coordination, which, if left unaddressed, could jeopardize the success of their projects.

Why are some collaborations impactful, fruitful, and lasting, while others fail (at times, spectacularly)? What factors help or hinder the effectiveness of teams? How do we assemble a highly productive team? Is there an optimal size for the team? How do teams evolve and dissolve over time, and how can they maintain and diversify their membership? And how do we assign credit for a team's work? In Part II, we focus on the rich body of literature that is often called the Science of Team Science (SciTS), examining how scientists collaborate and work together in teams. We start by asking a simple question: Do teams matter in science?

Chapter 2.1

The increasing dominance of teams in science

To what degree do teams dominate the production of science in the 21st century? The answer is provided by a study that explored the authorship of 19.9 million research articles and 2.1 million patents [2], revealing a nearly universal shift towards teams in all branches of science (Fig. 2.1.1a). For example, in 1955, nearly half of all science and engineering publications were by single authors, but by 2000, the number of solo-authored papers had dwindled dramatically, while team-authored papers now made up 80% of all publications. Importantly, the shift toward teams is not simply driven by the fact that the experimental challenges are becoming larger, more complex, and more expensive. Pencil-and-paper disciplines like mathematics and the social sciences exhibit the same patterns. Teams wrote only 17.5% of social science papers in 1955, but, by 2000, team-based papers became the majority, reaching 51.5%—witnessing the same trend toward teamwork as had been observed decades earlier in the natural sciences.

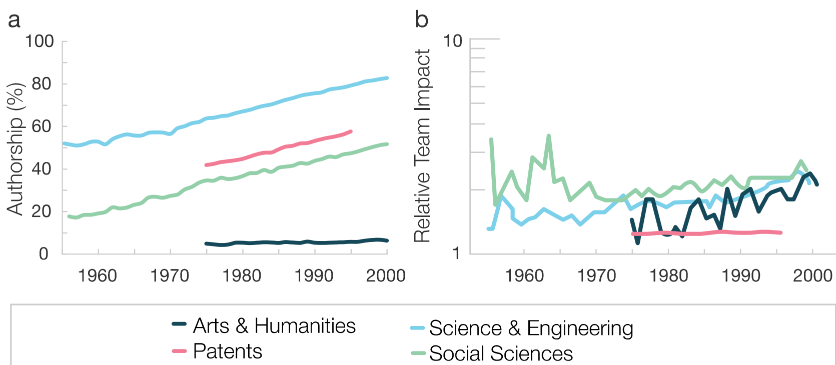

Figure 2.1.1 **The growing dominance of teams.** (a) Changes in the fraction of papers and patents written by teams over the past five decades. Each line represents the arithmetic average taken over all subfields in each year, with colors indicating different fields. (b) The Relative Team Impact (RTI) represents the mean number of citations received by team-authored work divided by the mean number of citations received by solo-authored work in the same field. A ratio of 1 implies that team- and solo-authored work have comparable impact. The lines present the arithmetic average of RTI in a given year for the entire field. After Wuchty *et al.* [2].

But perhaps more interesting than the trend itself is the kind of research that team work has produced. Teams do not merely produce more science; they are increasingly responsible for discoveries with larger impacts [2]. Indeed, on average, team-authored papers garner more citations than single-authored work at all points in time and across all broad research areas[2] (Fig. 2.1.1b).

The influence of teams is especially interesting if we focus exclusively on the very top tier of high-impact papers: Teams are increasingly responsible for producing the most important scientific hits. Indeed, whereas in the early 1950s, the most cited paper in a field was more likely to have been written by a lone author than a team, that pattern reversed decades ago [5]. Today in science and engineering a team-authored paper is 6.3 times more likely than a solo-authored paper to receive at least 1,000 citations. This pattern is even more pronounced in the arts, humanities, and patents, where since 1950s teams have *always* been more likely than individuals to produce the most influential work.

2.1.1 The Rise of Team Science

Why do teams dominate science to such a degree? One hypothesis is that teams excel in generating truly novel ideas. By grouping experts with diverse but specialized knowledge, teams give their members access to a broader pool of knowledge than any individual collaborator could have. By harnessing varied methodologies and bodies of research, teams are more capable of creating innovative combinations of ideas and concepts. Indeed, as we will learn in later chapters (Chapter 3.3), papers that introduce novel combinations while also remaining embedded in conventional thinking increase their chance of becoming hits by at least twofold [7]—and teams are 37.7% more likely than solo authors to insert novel combinations into familiar knowledge domains [7]. Since the greatest challenges of modern science often require interdisciplinary expertise, teams are emerging as the key innovation engine to produce tomorrow's breakthroughs.

For the individual researcher, there are also other benefits to working in teams [8]. For example, colleagues working together can bounce ideas off one another and check one another's work, aiding both

[2] It may be tempting to attribute the higher impact of team-authored papers to self-promotion: Authors like to cite their own work, so the more authors a paper has, the more citations it's guaranteed to get. Yet, the higher impact of team-authored paper remains unchanged if we remove self-citations [5, 6].

innovation and rigor. Collaboration also boosts the visibility of a researcher by exposing her publications to new coauthors and disciplines, resulting in a broader and more diverse audience. Additionally, teamwork not only leads to a wider readership, but also helps in securing funding for further research. Indeed, a study focusing on a sample of 2,034 faculty members at Stanford University over a 15-year period found that collaborations produce more grant submissions, are more likely to be awarded grants, and yield larger dollar amounts [9].

It is therefore not hard to imagine that the best and brightest scientists are those who are more willing to collaborate. In 1963, the sociologist Harriet Zuckerman set out to discover how outstanding scientists worked, interviewing 41 out of the 55 Nobel laureates living in the US at that time. She found that an internal bent toward teamwork seemed to be a trait that they all shared. The Nobel laureates were more willing to collaborate than their less prominent colleagues, which offered them a clear, long-term advantage in science [10].

Box 2.1.1 Ageless Teamwork. Collaboration in the creative space is not a modern invention. The *Yongle Encyclopedia*, or *Yongle dadian* ("The Great Canon of the Yongle Era"), is the world's largest paper-based encyclopedia, comprising 22,937 rolls or chapters in 11,095 volumes. Commissioned by the Yongle Emperor of the Ming dynasty in 1403 in China, it required the collaborative effort of 2,000 scholars over a period of five years.

Figure B2.1.1 The Yongle Encyclopedia, on display at The National Library of China in 2014.

2.1.2 The Drivers of Team Science

The recent explosion of teamwork can be attributed to two major trends.

First, as science grows increasingly complex, the instruments required to expand the frontier of knowledge have increased in scale and precision. For example, the Large Hadron Collider (LHC), the world's largest particle collider at CERN, is crucial for advances in particle physics. However, such a tool would be unaffordable to individual investigators or institutions. The LHC—both its conception and its financing—would have been unthinkable without teamwork. Over 10,000 scientists and engineers from over 100 countries contributed to the project. Hence collaboration is not just beneficial, it's *necessary*, forcing the community to pool resources together to help advance scientific understanding.

Second, the ever-broadening body of human knowledge is so vast that it is impossible for any one person to know everything. Even for those working in relatively small, esoteric fields, the burden of knowledge on successive generations of scientists is continually increasing. To cope, scientists often specialize, narrowing their focus in order to manage the knowledge base and to reach the frontiers of knowledge faster. Such specialization has led to the "death of the renaissance man" in science, a phenomenon documented in the context of inventions [11]. Indeed, data on consecutive patent applications filed by solo inventors show that individuals increasingly remain within a single technological area and demonstrate a decreased capacity to contribute new, unrelated inventions. Thus, as the burden of knowledge required to move between fields becomes more overwhelming, collaborations become one way to reach beyond one's own specialized subfield [11, 12]. In other words, scientists not only want to collaborate—they *have to*. Increasing specialization means that each person has an excellent command of one piece of the puzzle. But to address the complex problems faced by modern science, scientists need to bring these pieces together, melding diverse skill-sets and knowledge in ways that allow us to innovate.

2.1.3 The Death of Distance

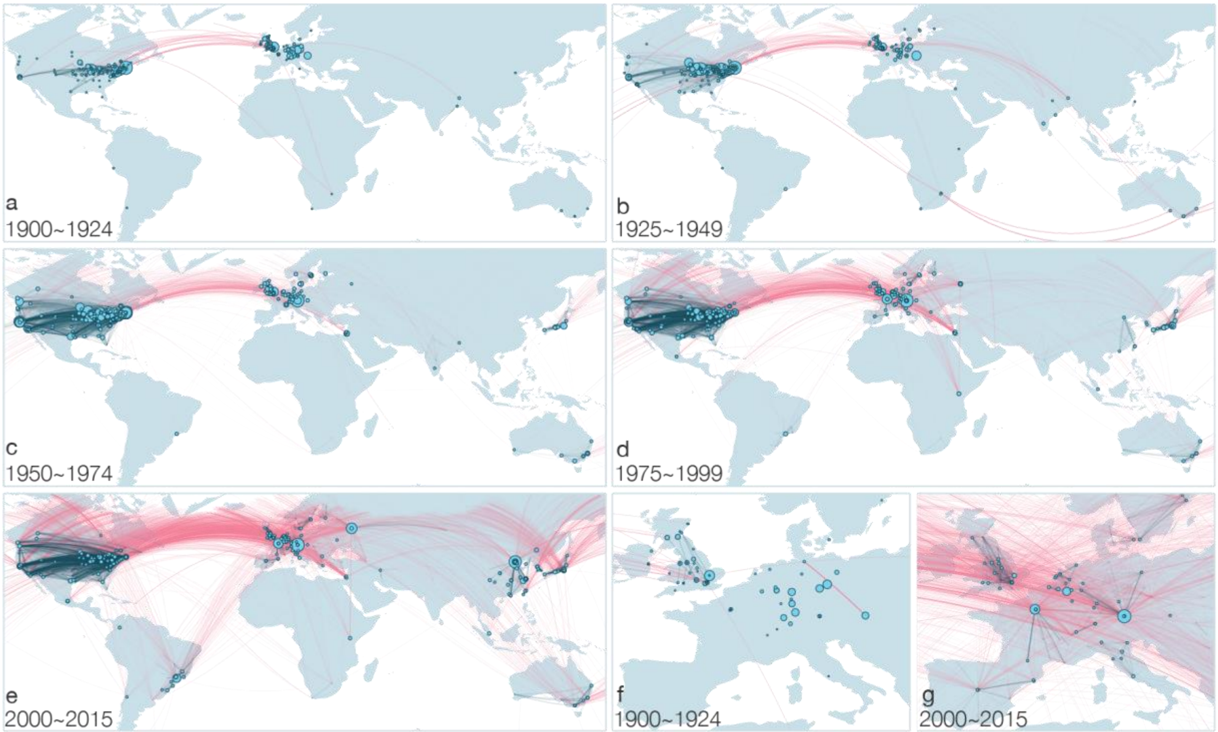

Figure 2.1.2 **A brief history of globalization of science collaborations**. The figure shows two types of collaborations: across institutions within the same country (green) and across institutions of different countries (blue). Between 1900–1924, collaborations across different institutions were prominent only in the US; international collaborations were mainly between the U.S. and the U.K. However, both types of collaborations were relatively weak. Between 1925–1949, international collaborations started to form between India and the U.K., as well as between Australia and the U.S. Due to World War II, and collaborations in Europe shrank during this period. Meanwhile, collaborative relationships in America were rapidly developing in the Midwest. Between 1950–1974, Israel and Japan started to engage in international teamwork. At the same time, the West Coast and the Southern United States became hubs of scientific collaboration. Between 1975–1999, Africa began to develop relationships with Europe. Surprisingly, within-institution collaborations in the U.S. decreased relative to those in Europe, although the absolute number of collaborations grew substantially over time for all countries. In the 21st century, more and more countries have risen to the international stage to collaborate extensively with others. After Dong 2017 [13].

With worldwide internet access and increasingly inexpensive transportation, it is now easier than ever to collaborate across borders, overcoming traditional geographical constraints (Fig. 2.1.2). Indeed, teams increasingly span institutional and national boundaries. Analyzing 4.2 million papers published between 1975 and 2005, researchers distinguished three types of authorship: solo authors, collaborators working at the same university, and collaborators who bridged the gap between institutions [14]. Of the three, collaborations between university faculty at different institutions was the fastest—and, in fact, the only steadily growing authorship structure. During the 30-year period examined, such inter-institutional collaborations quadrupled in science and engineering, reaching 32.8% of all papers published (Fig. 2.1.3a). The social sciences experienced similar trends, with their share of papers written in multi-university collaborations rising even more rapidly over the period and peaking at 34.4% (Fig. 2.1.3b).

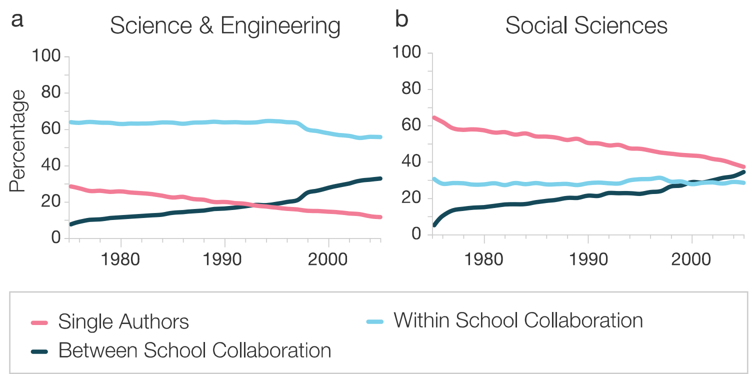

Figure 2.1.3 **The rise in multi-university collaboration**. By comparing the percentage of papers produced by different authorship combinations, the plots document the increasing share of multi-university collaborations between 1975 and 2005. This rise is especially strong in Science and Engineering (a) and Social Science (b), whereas it remains weak in Arts & Humanities, in which collaboration of any kind is rare [14]. The share of single-university collaborations remains roughly constant with time, whereas the share of solo-authored papers strongly declined in Science & Engineering and Social Sciences. After Jones *et al.* [14].

Teams today are increasingly spanning national boundaries as well. Worldwide, between 1988 and 2005, the share of publications with authors from multiple countries increased from 8% to 20% [15]. Another analysis of papers published between 1981 and 2012 calculated the balance of international and domestic research collaboration in different countries [16]. As shown in Fig. 2.1.4, while total research output has grown substantially over time, domestic output has flat-lined in the United States and in Western European countries. This means that these days, international collaborations fuel the growth of science in these countries. By contrast, in emerging economies, international collaborations have yet to match—much less eclipse—domestic output. The total volume of papers from China, Brazil, India, and South Korea has increased 20-fold, from fewer than 15,000 papers annually in 1981 to more than 300,000 papers in 2011. Yet, about 75% of the research output from these four countries remains entirely domestic (right column in Fig. 2.1.4).

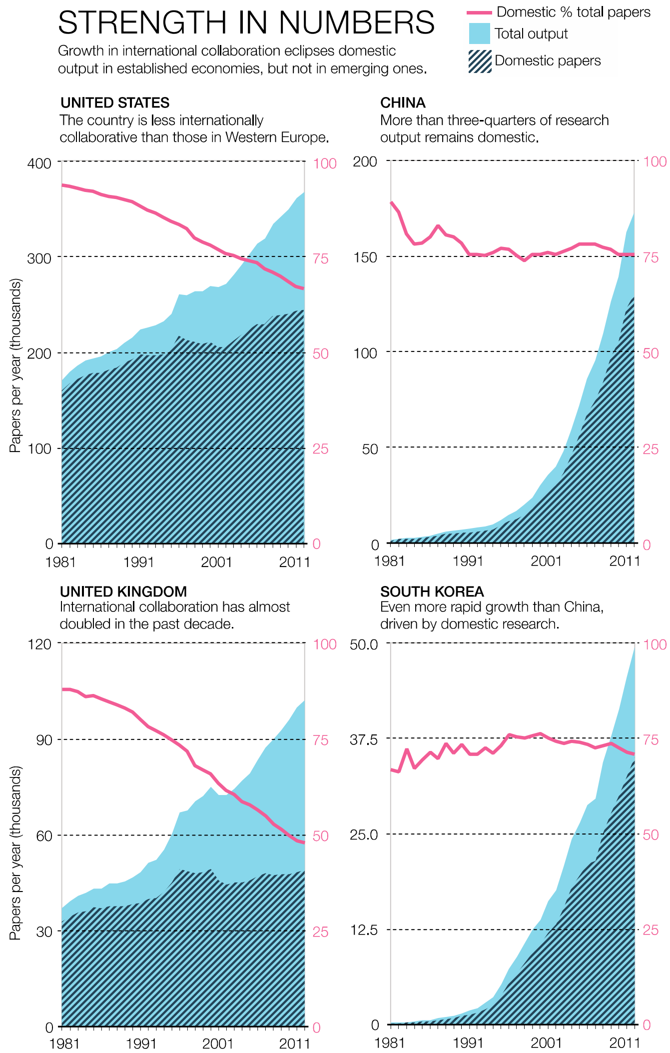

Figure 2.1.4 **The increasing role of international collaboration**. If a paper only contains authors whose addresses are from the home country, then it is counted as domestic output of that country. Comparing the left and right panels shows that growth in international collaboration eclipses the growth of domestic output in established economies, but not in emerging ones. After Adams [16].

The growth we see in international collaborations bodes well for a few reasons. We already know that citation impact is typically greater for teams than for solo authors. That benefit strengthens when the collaborators in question are either international [16] or between universities [14]. In both the U.K. and U.S., papers with shared international authorship are cited more than papers with only domestic authors. And the benefit appears to be growing—between 2001 and 2011, this "impact premium" rose in both countries by 20%. Multi-university collaborations have a similar impart advantage [14]: When an entire team comes from the same university, their probability of publishing a paper with above-average citations is around 32.7% in science and engineering and 34.1% in the social sciences. But, if the collaboration involves different institutions, that probability increases by 2.9% or 5.8%, respectively.

While the advantages of collaborations across geographies are clear, an important consequence of the "death of distance" in modern science is increasing inequality in both impact and access to resources [8, 17, 18]. Indeed, scientists often reach across university boundaries as they select coauthors, but rarely across university prestige levels. Researchers at elite universities are more likely to collaborate with scientists at other elite universities, and scientists at lower-ranked institutions tend to collaborate with researchers from institutions of comparable rank [14]. Hence, even as geographic distance loses its importance, the role of social distance is increasing. This kind of stratification among institutions may further intensify inequality for individual scientists.

Furthermore, the benefits of collaboration vary greatly based on a scientist's position in a collaboration network. For instance, if an African country devotes special funding to help its researchers collaborate with their U.S.-based colleagues, which American institution will the researchers approach first: an Ivy League university, or a small liberal-arts college? Unsurprisingly, they will likely seek out well-known researchers at elite institutions. That means successful scientists at prestigious institutions are more likely to benefit from the resources offered by the global collaborative networks. Given that multi-university publications have a larger impact than collaborations within the same university, and that researchers at elite universities are also more likely to engage in such cross-university collaborations, the production of outstanding science may become more and more concentrated at elite institutions [8, 14].

Although team science intensifies inequality for individual scientists and institutions, it has benefits across the globe [17]. Today, a successful scientist at a prestigious university in America or Europe can design studies to be carried out by collaborators in less-developed countries, such as China, where labor-intensive scientific work is less expensive. Such collaborations can offer mutual benefits and help reduce the gap in knowledge between more- and less-developed countries.

On the other hand, the globalization of science also has dire implications for "brain drain" [16], which may fuel a growing divide between international and domestic research. Indeed, as science becomes more international, every nation will be able to more easily connect to the same global knowledge base, making it possible for their brightest scientists to continue their research elsewhere. This, in turn, compromises human resources in science for individual nations. Therefore, understanding the nuanced dynamics of team science may be necessary for nations to stay competitive, helping them to retain and attract global talents amid the growing scarcity of truly able researchers.

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As we showed in this chapter, teams play an increasingly important role in driving the overall production of knowledge, as well as key breakthroughs. Once a rarity, team science has become a dominant force in science, a phenomenon that cannot be ignored by scientists, policy makers or funding agencies. Yet, despite the many benefits teamwork affords, there are also reasons to believe that teams are not optimized for discovery [3, 8, 19]. For example, while collaboration lends legitimacy to an idea—after all, a whole team needs to believe in a project to pursue it [19]—colleagues must reach consensus before they can move forward, a process which can hinder the group's headway. And while collaborations help researchers bridge disciplinary boundaries and generate new insights and hypotheses, the time and energy they must devote to coordination and communication can be costly, in some cases outweighing the benefits garnered by working collaboratively. This tradeoff is further complicated by the increased ambiguity about who should, and does, receive credit for the collaborative work. Indeed, strategically balancing these complex trade-offs is critical to building successful teams in science, and that's what we will discuss in the next chapters.

Chapter 2.2

The Invisible College

We tend to believe that rubbing shoulders with the top performers in their field will also make us great. But do our peers truly make us better scientists? In the previous chapter, we have explored how collaboration influences the impact of a project. But how does collaboration influence the productivity and the impact of individual scientist? This question encompasses a broader set of problems, known in the economics literature as “peer effects” [20-23]. To see how powerful peer effects can be, let’s visit the dormitories at Dartmouth College [21].

Freshmen entering Dartmouth College are randomly assigned to dorms and to roommates. However, a study found that when students with low grade-point averages (GPA) were assigned to a room with higher-scoring students, their grades improved. Since students with different majors lived together, we can’t attribute the improvement to something like weaker students getting help from their roommates on shared coursework. Rather, they became better students *because* they were surrounded by higher-performing peers.

Peer effects also come into play when people work together towards common goals. Indeed, over the past 20 years, numerous studies have documented peer effects in diverse occupations, from fruit pickers, to supermarket cashiers, to physicians, to sales teams, and more [23]. For example, examining a national supermarket chain, researchers found that when a less productive cashier was replaced with a more productive cashier on a shift, other cashiers on the same shift scanned items more quickly [22]. This change in behavior seems counterintuitive—after all, if a star cashier replaces a slower scanner, other cashiers could simply take it easy, engaging in the so-called “free riding” phenomenon. Yet, the cashiers acted in the exact opposite way: The presence of their productive peer nudged them to enhance their performance.

Understanding how we are influenced by others is important, because it could unleash social multiplier effects, eventually improving everyone's outcome. Consider again the college dorm example: If the academic performance of some students improves, then their improved performance could in turn improve the outcomes of others in their respective peer groups and continue rippling out to more and more students.

But do peer effects exist in science? And if so, how can students, scientists, administrators, and policy makers take advantage of them?

Box 2.2.1 Mencius's mother, three moves.

The Chinese philosopher, Mencius (372—289 BC), is the most famous Confucian after Confucius himself. One of the most famous Chinese four-character idioms is Meng Mu San Qian, meaning "Mencius's mother, three moves" a phrase that captures one of the earliest examples of peer influence. It describes why Mencius's mother moved houses three times before finding a place she felt was suitable for her child's upbringing. Mencius's father died when he was little, so Mencius's mother, Zhang, raised Mencius alone. Poor as they were, their first home was next to a cemetery, where people loudly mourned for the dead. Soon Mencius's mother noticed that her son had started to imitate the paid mourners. Horrified, she decided to move near a market in town. It wasn't long before the young Mencius began to imitate the cries of merchants, a profession of ill-repute in early China. So, Zhang, distraught, decided to move again, this time landing in a house next to a school. There Mencius began to spend time with the students and scholars, imitating their habits and becoming more focused on his own studies. Pleased to see such behavior in her son, and attributing it to his proximity to the scholars, Zhang decided to make the house by the school her permanent home, ensuring that Mencius would become Mencius.

2.2.1 A bright ambiance

Following numerous interviews with Nobel laureates, Robert Merton noted the "bright ambiance" that such star scientists often provide [24]. That is, star scientists not only achieve excellence themselves; they also have the capacity to evoke excellence in others. We may measure this capacity by examining changes in a department after it hires a new star scientist. In one study, researchers traced the publication and citation records of each member of a department after a star scientist arrived, examining 255 evolutionary biology departments and 149,947 articles written by their members between 1980 and 2008 [25]. They found that after a star arrived, the department-level output (measured in number of publications, with each paper weighted by its citation count) increased by 54%. This increase could not be attributed to the publications of the stars themselves: After removing the direct contributions of the star, the output of the department *still* increased by 48%. In other words, much of the observed gains came from the increased productivity of the colleagues who'd been there before the star arrived. And importantly, the productivity gain persisted over time: Even eight years after the star's arrival, the productivity of her colleagues had not diminished.

It's worth noting that those individuals in the department whose research was the most related to the star—i.e., those who have cited her papers before—saw the biggest boost in productivity. By contrast, colleagues whose research was unrelated to the new hire were far less influenced.

Yet the star's biggest contribution to her new department comes not in productivity increases but in the quality of future hires. Indeed, the quality of subsequent faculty hires (measured by the average citations of papers published by a scientist at the time she joined the department) jumped by 68% after the arrival of a star. Differentiating again between the new hires related and unrelated to the star's research, the quality of related new hires increased by a staggering 434%. Furthermore, the quality of unrelated new hires also increased by 48%. It seems that stars not only shine on their peers, prompting them to succeed, but also attract other future stars to join them.

Box 2.2.2 Causal inference for peer effects.

In observational studies, i.e., those that rely on pre-existing datasets to draw conclusions, peer effects are uniquely difficult to quantify, hence insights obtained in such data-driven studies must be interpreted with care. For instance, in the star scientist study discussed above, other factors may have also contributed to the observed changes. Is it possible, for example, that stars do not *cause* the rise in productivity, but rather they are attracted to already-improving departments? Or could it be that an unobserved variable, like a positive shock to department resources (e.g., philanthropic gifts, increase in government funding, the construction of a new building) offered the opportunity for the department to hire a star—and that the same shock increased its incumbent productivity and the quality of subsequent recruits?

The challenge of identifying causal evidence for peer effects is widespread, and by no means limited to the study mentioned above [26]. Indeed, in social sciences, this is commonly known as "reflection problem" [20]. Imagine two students, Allen and Mark. Allen started to hang out with Mark, the better student, and we later observe that Allen improved his grades. Did Allen do well *because* Mark had a good influence on him? Not necessarily. At least three other mechanisms could be at play:

- It is just as plausible to think that Allen chose to hang out with Mark because he was also a good student. This phenomenon is called the "selection effect": individuals generally self-select into groups of peers, making it difficult to separate out any actual peer effect.

- Allen and Mark can affect each other simultaneously, making it difficult to single out the impact Mark's outcome has on Allen's outcome.

- The observed improvement in Allen's grades can be induced by common confounding factors that we cannot observe. For example, Allen may have improved his grades simply because a new teacher or a better after-school program came along.

Given these challenges, we often rely on randomized experiments to tease out peer effects. This is the key concept behind the Dartmouth dorm study, where students were assigned randomly into different rooms, thereby eliminating most alternative explanations. Alternatively, we may rely on external, unexpected shocks to a system for a so-called "natural experiment." If there is a sudden change in one parameter while other variables remain the same, we can be more certain that the response of the system is a pure response to the external shock. We will cover one such an example in the next section, where researchers use the unexpected deaths of star scientists to quantify their influence on their colleagues' productivity and impact.

2.2.2 The Invisible College

The examples of students and cashiers suggest that peer effects are most prominent when individuals interact directly with their peers. For example, the improvement of students' GPA was only detectable at the individual room level, but absent at the dorm level [21]. In other words, an exceptional student had no influence on the performance of a neighbor down the hall. Similarly, the cashiers who became more productive were the ones who could see their star peer joining the shift. Others on the same shift who were not aware of the shift change continued at their normal pace [22]. What's particularly interesting in science, however, is that many of the observed peer effects are not limited to physical proximity. Rather, they transcend the physical space, extending into the world of ideas. To demonstrate this, let's look at what happens when superstar scientists die suddenly and unexpectedly.

In one study, researchers examined how the productivity and impact of a superstar scientist's coauthors (measured by publications, citations, and grants from the National Institutes of Health) changed when their high-performing collaborator suddenly passed away [27]. Following a superstar's death, her collaborators experienced a lasting 5% to 8% decline in their quality-adjusted publication rates. Interestingly, these effects appear to be driven primarily by the loss of an irreplaceable source of ideas rather than a social or physical proximity. Indeed, coauthors who worked on similar topics experienced a sharper decline in output than those coauthors who worked on topics further afield. And when a superstar's collaborator was heavily cited, she tended to experience a steeper decline in productivity than the superstar's less renowned collaborators. These results together provide evidence of what 17th century scientist Robert Boyle called an "invisible college" of scientists, bound together by interests in specific scientific topics and ideas—a college which suffers a permanent and reverberating intellectual loss when a star is lost.

Similar effects were observed after the collapse of the Soviet Union, when the country experienced a mass emigration of Soviet scientists. Researchers studied the output of mathematicians who remained in Russia, examining what happened when their coauthors suddenly fled to other countries [28]. They found that the emigration of an *average* colleague or collaborator did not affect the productivity of those he left behind. In fact, some of his former colleagues even enjoyed a modest boost in their output, perhaps because the loss improved opportunities for those who remained. However, when researchers inspected the loss of very high-quality collaborators, measured by productivity in their fields, they uncovered major consequences. Ranking authors according to the quality of their collaborators, they found that the top 5% of authors suffered an 8% decline in publications for every 10% of their collaborators who had emigrated. This suggests that while we may manage the loss of an average collaborator, losing an outstanding one is, however, highly detrimental.

This finding is consistent with research examining the peer effects on science professors in Germany, after the Nazi government dismissed their colleagues between 1925 and 1938 [29]. The loss of a coauthor of average quality reduced a German professor's productivity by about 13% in physics and 16.5% in chemistry. But, once again, the loss of the higher-than-average coauthors led to a much larger productivity loss. To be clear, these coauthors were not necessarily colleagues in the same university but were often located in different institutions and cities across Germany. Once again, these results speak to the idea that, at least in science, the "invisible college" is as important as the formal college in which we reside [30].

Box 2.2.3 The helpful scientists. Star scientists are typically defined by their individual productivity and output, such as, citations, publications, patents, and research funding [31]. But do these qualities accurately capture a scientist's value to an institution? What kind of scientist should a department hire—an investigator who churns out high-impact papers in quick succession, yet rarely finds the time to show up to department meetings? Or a researcher who works at a slower pace but who is willing to problem-solve departmental concerns, attend seminars, and offer feedback on colleagues' unpublished works?

It appears that both are critical in different ways. Indeed, we have seen the significant impact that a "star" scientist can have on colleagues' productivity, and on new hires. But research shows that the "helpful" scientist also has something important, but distinct, to offer.

For example, a study examining the acknowledgment sections of papers identified "helpful" scientists as those who were frequently thanked by others [32]. When these helpful scientists died unexpectedly, the quality (though not the quantity) of their collaborators' papers dropped precipitously. By contrast, the study found no such decline after the deaths of less helpful scientists. In addition, scientists who provided conceptual feedback—namely, critiques and advice—had a more significant impact on their coauthors' performance than those who provided help with material access, scientific tools, or technical work. It seems that there is often an invisible social dimension to performance. Being helpful and collegial is not merely a nice thing to do—it can genuinely affect the quality of scientific output of your colleagues.

In this chapter, we have demonstrated the highly connected nature of science, showing how a scientist's productivity and creativity depends on her network of collaborators and colleagues. As much as we emphasize individual talent and celebrate independent thought in science, the fact is that scientists are highly dependent upon each other. Indeed, our productivity is strongly influenced by our departmental colleagues, regardless of whether they collaborate with us directly, or whether their research is merely related to what we do. Most importantly, we are not just influenced by our next-door neighbors. However far away our collaborators might be, their achievements can propagate through the network of ideas to produce long-lasting effects on our own careers. In other words, the idea of the lone genius was never accurate—in science we are never alone.

Chapter 2.3

Coauthorship Networks

Throughout history, only eight mathematicians have published more than 500 papers. Lucien Godeaux (1887–1975) is one of them [33]. A prolific Belgian mathematician, he's ranked fifth among the most published in history. Sitting on the very top of this list is Paul Erdős, the Hungarian mathematician we encountered in Chapter 2.1.

There is, however, a fundamental difference between Godeaux and Erdős. Of the 644 papers published by Godeaux, he was the sole author on 643 of them. In other words, only *once in his career* did he venture out of his lonely pursuit of mathematics and coauthor a paper with someone else. Erdős, on the other hand, is famous not only for his unparalleled productivity, but also for the more than 500 coauthors with whom he worked throughout his career. Indeed, most of Erdős' papers were the fruit of collaborations—so much so that they inspired the so-called "Erdős number," a popular pastime of mathematicians curious about their distance to this giant of mathematics.

Erdős, by definition, has an Erdős number of zero. Those who have coauthored at least one paper with Erdős are given an Erdős number of 1. Those who have coauthored with these people but not with Erdős himself have an Erdős number of 2, and so forth. It is an unparalleled honor to have an Erdős number of 1, or, in other words, to be counted among his plentiful but still rarified list of collaborators. Short of that, it's a great distinction to be only two links away from him. In fact, having a relatively small Erdős number gives a person bragging rights not only in mathematics, but in many different disciplines—it's not unusual for scientists of all kinds to have that prized numeral listed, only partially in jest, on their CVs and websites.

The very existence of the Erdős number demonstrates how the scientific community forms a highly interconnected web, linking scientists to one another through the papers they have collaborated on. This web is often referred to as the coauthorship network. But is there a pattern underlying the way we collaborate? Which kinds of scientists are most, or least, willing to collaborate with one another? Understanding coauthorship networks, and the insights they reveal about the structure and the evolution of science, is the focus of this chapter.

2.3.1 A first look at coauthorship network

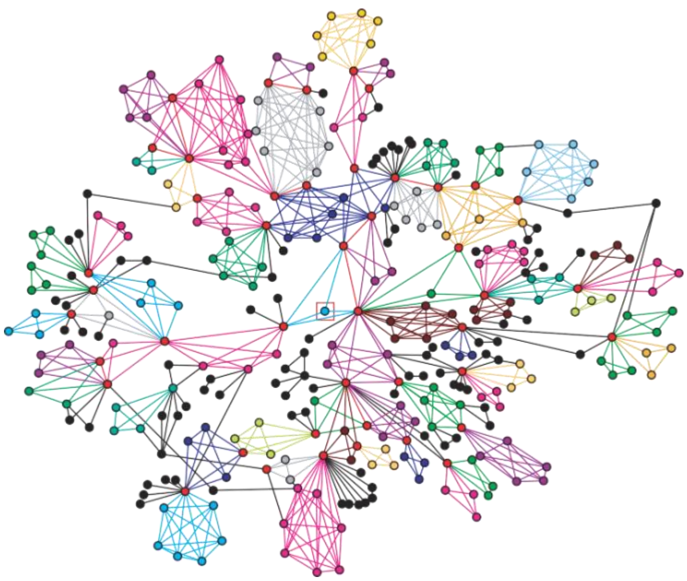


Figure 2.3.1 **Co-authorship network.** The figure shows the local structure of the co-authorship network between physicists in the vicinity of a randomly chosen individual (marked by a red frame). The network is constructed based on papers from Cornell University's archive server (cond-mat), the precursor of the widely used arXiv, containing at that time over 30,000 authors. Each node is a scientist, and links document collaborative relationships in the form of co-authored publications. The color-coded communities represent groups of collaborators that belong to locally densely interconnected parts within the network. Black nodes/edges mark those scientists that do not belong to any community. After Palla *et al.* [34].

As soon as massive digitized publication records became available around 2000, researchers started constructing large-scale coauthorship networks, capturing collaborative patterns within mathematics [35-38], biology [38], physics [34, 38], computer science [39] and neuroscience [37]. To construct a coauthorship network, we go through each publication and add a link between two scientists if they appeared on the same paper together. Figure 2.3.1 illustrates the local structure of one such network surrounding a randomly selected author, highlighted in the center [34]. A quick look at this network reveals several important features of collaborations: First, the network is held together by a few highly connected nodes, or hubs, who are highly collaborative individuals like Erdős. Second, the network consists of densely connected cliques of authors or communities. To highlight these communities, we can apply to this network a community-finding algorithm designed to identify cliques [34], and color the nodes based on whether they belong to a clearly identifiable clique. Those that do not belong to any recognizable community are colored black. As the figure illustrates, the vast majority of nodes take up a color, indicating that most scientists belong to at least one identifiable community.

2.3.2 The number of collaborators

With more than 500 coauthors within mathematics, Erdős is clearly an outlier. But how unusual is he for a mathematician? To find out, next we compare the collaboration networks across biology, physics, and mathematics [38]. A key property of a node in a network is its *degree*, which represents the number of links it has to other nodes [40, 41]. In the context of the coauthorship network, the degree k_i of node i represents the number of collaborators scientist i has. The distribution of the number of collaborators that scientists have in each of the three disciplines, $P(k)$, is shown in Fig. 2.3.2. Each of these distributions is fat-tailed, indicating that, regardless of their discipline, almost all scientists work with only a few coauthors, while a rare fraction accumulates an enormous number of collaborators. But, though all three distributions shown in Fig. 2.3.2 are fat-tailed, the curves follow distinct patterns. Indeed, the distribution for biology (blue) has a longer tail, reflecting the higher likelihood that a biologist will have a large number of collaborators, whereas the distribution for mathematics (green) decays the fastest among the three. Hence, highly collaborative individuals are somewhat common in biology, but are especially rare in mathematics—and an ultra-collaborator like Erdős is rare in any discipline.

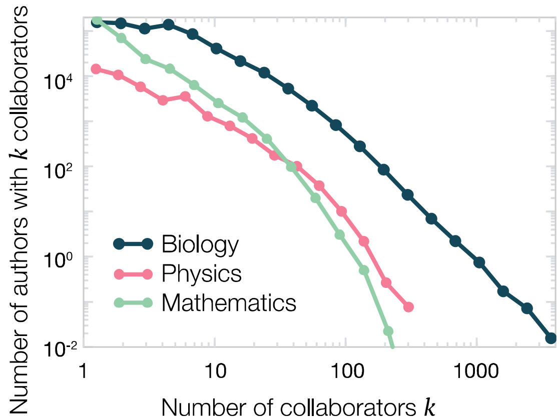


Figure 2.3.2 **Collaboration Networks are Scale-free.** The plots show the distribution of numbers of collaborators for scientists in physics, biology and mathematics, indicating that the underlying distribution are fat tailed. This implies that the collaboration network is scale-free [40, 41], meaning that the degrees can be approximated by a power law distribution. After Newman *et al.* [38].

Importantly, the number of collaborators an individual has already worked with can predict her odds of establishing new collaborations in the future. That's the idea of preferential attachment, a concept we will discuss again in Part 3, stating that we are more likely to collaborate with highly collaborative individuals. Indeed, when an author publishes for the first time, odds are she'll be co-authoring her paper with senior authors, such as her advisor, someone who already has a large number of co-authors, rather than a fellow graduate student, who likely lacks collaboration links [37]. The same is true for new collaborations among scientists who are already part of the network: they are more likely to form new links to highly connected authors than less connected ones. As a consequence of preferential attachment, authors with more collaborators gradually increase their circles of collaborators, gradually turning into hubs of the scientific collaboration network.

2.3.3 Small world

As word of the Erdős number spread, mathematicians around the world began to calculate their distance from the esoteric center of the math universe. Their efforts were documented by Jerry Grossman, a math professor at Oakland University in Rochester, Michigan, who maintains the Erdős Number Project [42]. If you visit the project's website, you soon realize that the Erdős number extends well beyond mathematics. Listed next to mathematicians are economists, physicists, biologists, and computer scientists who can claim a link to Erdős. Bill Gates is there, for example, thanks to his 1979 publication with Christos H. Papadimitriou, who in turn published with Xiao Tie Deng, who in turn published with Erdős' coauthor Pavol Hell. That means that Gates has an Erdős number of 4. That may sound like a small number of steps to connect a Hungarian mathematician to someone who almost never engages in scientific publishing. But, as we will see, the paths between scientists are often shorter than we might have imagined.

This kind of far-flung yet proximal connection has to do with the small-world phenomenon [43], also known as "six degrees of separation" (Box 2.3.1). Put in network science terms, this popular concept captures the fact that there is a short path between most pairs of nodes within a network. Indeed, if we measure the minimum number of links that separate any two scientists in a coauthorship network, the typical distance is about six links. This pattern holds for biologists, physicists, computer scientists [39], mathematicians and neuroscientists [37]. That means that if one scientist picks another random scientist, even one she has never heard of, chances are that she will be able to connect to this person through just five or six co-authorship links. Moreover, the distance between a typical scientist and a highly connected hub of the collaboration network is even smaller. For instance, the average distance from Paul Erdős to other mathematicians is about 4.7 [42], significantly lower than the typical distance in the network as a whole.

Box 2.3.1 Six degrees of separation. The small-world phenomenon is also known as *six degrees of separation*, after John Guare's 1990 Broadway play. In the words of one of the play's characters: "Everybody on this planet is separated by only six other people. Six degrees of separation. Between us and everybody else on this planet. The president of the United States. A gondolier in Venice... It's not just big names. It's anyone. A native in a rain forest. A Tierra del Fuegan. An Eskimo. I am bound to everyone on this planet by a trail of six people. It's a profound thought."

Because research teams are embedded in the co-authorship network, the size and shape of that network can affect how teams perform. In an enormous, far-flung network, many teams will be more than six steps apart, leaving their members isolated and unable to easily exchange new ideas. On the other hand, if the world of collaborations is too small, it can form an echo chamber that is detrimental to out-of-the-box thinking. That means there may be a sweet spot in the middle which provides creative collaborators with the most advantageous environment for nurturing creative ideas. Indeed, this relationship between a team's creativity and the structure of the collaboration network is well documented in the context of Broadway musicals [44].

To understand how "small-worldliness" affects a team's creativity, we can explore the collaboration patterns of the creative artists involved in the production of Broadway musicals, [44]. In the Broadway network, two artists are connected if they worked together in a musical before, either as producers, directors, designers, or actors. Figure 2.3.3 shows three networks of teams characterized by varying degrees of the small-world property. Let's use *W* to denote the "small-worldliness" of each network. The map on the left of Fig. 1.3 shows a "big world" and low-*W* where the artists are removed from one another, due to the sparseness of the links between the different teams. By contrast, the network on the right is more densely connected (high *Q*).

Measuring each team's performance based on box office earnings (financial success) as well as the average of the critics' reviews of their musical (artistic success), researchers found that *W* correlates with team performance. When a team is embedded in a low-*W* network, the creative artists are less likely to develop successful shows. Given the few links between the teams, a production team is unlikely to exchange creative ideas with many others in the network. As *W* increases, the network of artists becomes more connected and cohesive, facilitating the flow of creative material across clusters. This increased information flow can make the exchange of tips and conventions more likely and provide artists with feedback that empowers them to take bigger risks, boosting the performance of teams embedded in the network.

But only to a certain degree. The same study shows that too much connectivity and cohesion (high *W* network) can also become a liability for creativity. Indeed, cohesive cliques tend to overlook useful information that contradicts their shared understandings. Taken together, that data indicates that on Broadway, teams perform best when the network they inhabit is neither too big, nor too small.

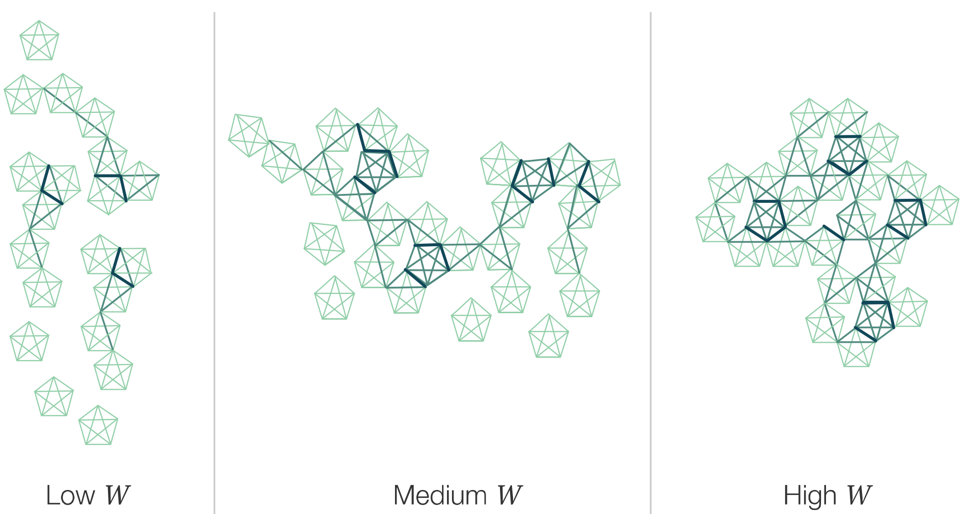


Figure 2.3.3 **Small worlds and team performance.** Diagrams of networks of Broadway artists illustrate the role of the small world effect on team performance. The parameter *W* quantifies the "small-worldiness" of a network. When *W* is low, there are few links between teams (cliques), resulting in a network of low connectivity and cohesion. As *W* increases, there are many between-team links, resulting in high connectivity and cohesion in the network's topology. At medium levels of *W* the small world network offers an optimal amount of connectivity and cohesion. After Uzzi and Spiro [44].

2.3.4 Connected components

The fact that Bill Gates has a small Erdős number (four) prompts a broader question: Why does Gates even have an Erdős number? After all, for Gates to have an Erdős number, there must exist a path on the coauthorship network between Gates and Erdős. If there is no such a path, then Gates would have an Erdős number of infinity. The fact that Gates has an Erdős number at all indicates that he and Erdős are on the same "connected component" of the collaboration network. In general, a *connected component* represents a group of nodes that are all connected to one another through paths of intermediate nodes. One key property of real coauthorship network is its *connectedness*; almost everyone in the community is connected to almost everyone else by some path of intermediate coauthors. For example, if we count the connected components within the three networks used in the study shown in Fig. 2.3.2, we will find that the largest connected component contains around 80 or 90% of all authors. A large connected component speaks to the idea of the invisible college, the web of social and professional contacts linking scientists across universities and continents, creating intellectual communities of shared values and knowledge base.

The fact that so many scientists are a part of the same connected component lets us draw several conclusions. First, and most obviously, it means that scientists collaborate. But if scientists always collaborate with the same set of coauthors, the network would be fragmented into small cliques isolated from each other, representing isolated schools of thought, like the low-*W* network seen in Fig. 2.3.3. Luckily, our invisible college is an expansive one. But what holds together more than 80% of all scientists in the same coauthorship network? Understanding the roots of this process reveals fundamental insights into how teams are assembled. To unpack these rules, let's first pay a visit to a chicken coop.

Chapter 2.4

Team Assembly

William M. Muir, a professor of animal sciences at Purdue University, thinks about team productivity in a different context: chickens [45]. Specifically, Muir wanted to know whether he could group hens into different cages to maximize the number of eggs they lay. Could he, in other words, assemble highly productive teams? That question is much easier to answer with chickens than with humans, partly because Muir didn't need a hen's permission to move her around. Plus, performance in this context is easy to measure—all you need to do is to count the eggs.

Muir assembled two types of cages. First, he identified the most productive hen from each cage and put them together in the same cage, creating a select group of "super-chickens." Then Muir identified the most productive *cage*—a group of hens that had produced a lot of eggs as a team, although not necessarily as individuals—and left it intact. How much better would the off-spring of the super-chickens do than the most productive existing team? To find out, he let both groups breed for six generations (a standard procedure in animal science), after which he tallied the eggs.

Six generations in, his control group of chickens from the highly productive cage were doing just fine. They were a brood of healthy, plump, and fully feathered birds, and their egg production had increased dramatically over the generations. What about the super-chickens? When Muir presented his results at a scientific conference, he showed a slide of the descendants of his carefully selected top-performers [46]. The audience gasped. After six generations, the number of chickens in the cage had dwindled from nine to three. The rest had been murdered by their coop-mates. And the once-stunning egg production of their foremothers was a thing of the past. The surviving descendants of the super-chickens, now sickly and pocked with battle scars, were under so much stress that they barely laid any eggs.

We assume, wrongly, that creating a successful team is as simple as recruiting the best of the best. Muir's experiment with chickens is an important reminder that there's far more to it than that. Sure, you need talented teammates, but they also must learn to work together, "to achieve something beyond the capabilities of individuals working alone" [47]. Indeed, just like recipes that produce a memorable dish, team assembly is not just about tossing the best ingredients you find in your fridge into a pot. We also need to consider how these ingredients fit together.

So how can scientists leverage singular talents without harming the greater team dynamic? Why are some teams exceptionally successful, winning in a seemingly predictable manner, while some teams flop, even when they're brimming with talent? Over the years, several reproducible patterns have emerged, which can help us understand and predict the success and failure of scientific teams.

2.4.1 Is there such a thing as "too much talent"?

When it comes to humans, should we really be concerned about having too much talent on a team? We tend to think, just as Muir did, that when we group top-performers together, we'll get excellent team performance. We even have a name for this approach: the "all-star team." At the very least, an all-star team should create a critical mass, the typical thinking goes, helping us to attract even greater talents. To see if this is the case, let's look at the Duke University English department.

If there has ever been an all-star academic team, it was Duke's English department in the late 1980s and early 1990s [48, 49]. Hoping to raise Duke's profile, university administrators decided to recruit the cream of the crop. They started by hiring Frank Lentricchia, then the most famous graduate of the department, away from Rice University in 1984. Next, at Lentricchia's suggestion, the administration recruited Stanley Fish from Johns Hopkins to head the department. His chairmanship would go on to become legendary for the uncompromising and expensive recruiting efforts Fish undertook. Indeed, Fish had a knack for hiring scholars who were stars or about to become stars. In just a few years, he lured outstanding professors from everywhere: Barbara Herrnstein Smith, who was about to become president of the Modern Language Association; Guggenheim fellow Janice Radway; pioneering queer theorists Eve Kosofsky

Sedgwick, Jonathan Goldberg, and Michael Moon; future African-American studies institution builder Henry Louis Gates Jr.; along with pioneering medieval literature scholar Lee Patterson and his influential wife, Annabel Patterson.

All of a sudden, Fish turned a respectable but staid English department into a who's who of the literary world. And these moves made an impact: Between 1985 and 1991, graduate applications increased four-fold. In the area of gender and literature, U.S. News and World Report would eventually rank the graduate program first in the country. When an external review committee came in 1992, their reports were filled with nothing but admiration: "We were struck by the chorus of testimony we heard from faculty outside the department that English has become a kind of engine or life-pump for the humanities at Duke, a supplier of intellectual energy and stimulation for the university at large. It is not easy to produce changes of this sort."

One can only imagine how shocked the external review committee members were when they came back merely six years later for their routine evaluation. By the end of spring 1997, Sedgwick, Moon, and Goldberg had accepted offers elsewhere; *American Literature* editor Cathy N. Davidson had resigned her professorship to join the university administration; Lee Patterson and his wife had defected to Yale. Although Lentricchia remained at Duke, he had left the department and publicly denounced his field. Fish, the man who started Duke's empire, also made plans of his own, announcing in July that he and his wife, Americanist Jane Tompkins, were leaving for the University of Illinois at Chicago, where he would serve as dean of the College of Arts and Sciences. By then, Tompkins had practically quit teaching, working instead as a cook at a local restaurant. Alas, it seemed that professors in the all-star department had not been busy with research or teaching, but with waging ego-fueled wars against one another. The dramatic demise of the once-great department landed on the front page of the *New York Times*, sealing its tarnished legacy [48].

What unfolded in Duke's English department is often described by psychologists as the *too-much-talent effect* [50], and it applies to several other team settings as well. For example, teams composed exclusively of high-testosterone individuals experience reduced performance because group members fight for dominance [51]. Having a large proportion of high-status members can also negatively affect the performance of financial research teams [52]. Make no mistake, highly talented individuals remain critical to team success. A large body of research confirms that adding more talents to the team can help improve outcomes—but only to a certain extent, beyond which the benefits may not be guaranteed.

So, when does “all-star” become “too-much-talent”? A comparison of team performance across different sports may offer some initial answers. Using real-world sports data, researchers found that in both basketball and soccer, the teams with the greatest proportion of elite athletes performed worse than those with more moderate proportions of top players [50]. In baseball, however, extreme accumulation of top talent did not have the same negative effect. The difference may be rooted in the fact that baseball depends far less on coordination and task interdependence between team members than either basketball or soccer. This evidence suggests that the transition from “all-star” to “too-much-talent” may be particularly pronounced when teams require members to work together as a cohesive unit.

Applied to science, the implications of these findings are obvious: There are few endeavors that require more coordinated, interdependent, and harmonious teamwork than scientific collaborations. This suggests that, scientists should take care not to overstuff their teams with all-stars, lest they suffer the same fate as an overloaded soccer team or the Duke English department.

2.4.2 The right balance

Assembling a successful team is not just about finding talents, but about choosing team members who offer the right balance of traits. But how do we find the right balance? Are we better off working with people whom we are familiar with, since they “speak our language,” allowing us to march forward in harmonious lockstep? Or should we pick collaborators who bring experience, expertise, and know-how quite different from our own, so that, together, we can tackle problems that none of us can solve alone? These are some of the most studied questions in the literature of team science, attracting researchers in disciplines ranging from psychology to economics to sociology [3]. Often this research hinges on the assumption that greater heterogeneity within a team leads to more diverse perspectives, which, in turn, leads to better outcomes. Yet at the same time, there are reasons to believe that diversity may not always be a good thing. For example, although diversity may potentially spur creativity, it can also promote conflict and miscommunication [53]. It therefore begs the question: does diversity in scientific collaborations hurt or help?

Recent studies have examined many different dimensions of diversity, including nationality, ethnicity, institution, gender, academic age and disciplinary backgrounds. These studies offer consistent evidence that diversity within a scientific team promotes the effectiveness of the team, either by enhancing productivity or resulting in works with higher impact, or both. Let us briefly review a few key findings in this domain:

- *Ethnic Diversity*: Using ethnicity as a measure of diversity, researchers found that diversity, or lack thereof, strongly influences both how much we publish and the impact of those publications [54, 55]. In general, authors with English surnames were disproportionately likely to co-author papers with other authors with English surnames and those with Chinese names were more likely to collaborate with other Chinese scientists. The papers that result from such homophily, however, tend to land in lower impact journals and garner fewer citations. Indeed, when researchers studied the ethnic diversity of over 2.5 million research papers written by US-based authors from 1985 to 2008, they showed that papers with four or five authors from different ethnicities had, on average, 5-10% more citations than those written by authors all of the same ethnicity [54, 55].
- *International Diversity*: A similar effect holds for international diversity [55, 56]. Analyses of all papers published between 1996 and 2012 in eight disciplines showed that papers authored by scientists from more countries are more likely to be published by higher-impact journals and tend to receive more citations [56].
- *Institutional Diversity*: Teaming up with someone from another institution also seems to reliably improve productivity and result in highly cited work, compared to teaming up with someone down the corridor [5, 14, 55]. Examining 4.2 million papers published over three decades, researchers [14] found that across virtually all fields of science, engineering, and social science, multi-university collaborations consistently have a citation advantage over within-school collaborations.

Interestingly, across various measures of diversity, ethnic diversity of a team seems to offer the most significant lift in the impact of their papers. A group of researchers analyzed over 9 million papers authored by 6 million scientists to study the relationship between research impact and five classes of team diversity: ethnicity, discipline, gender, affiliation, and academic age [57]. When they plotted those diversity measures against the teams' five-year citation counts, ethnic diversity correlated with impact more strongly than did any other category (Fig. 2.4.1 Panel a). The researchers further showed that ethnic diversity, not some other factor, was indeed behind this impact boost. Indeed, even when they controlled for publication year, number of authors, field of study, author impact level prior to publication, and university ranking, the clear association between diversity and scientific impact remained: Ethnic diversity on a team was associated with an impact gain of 10.63%.

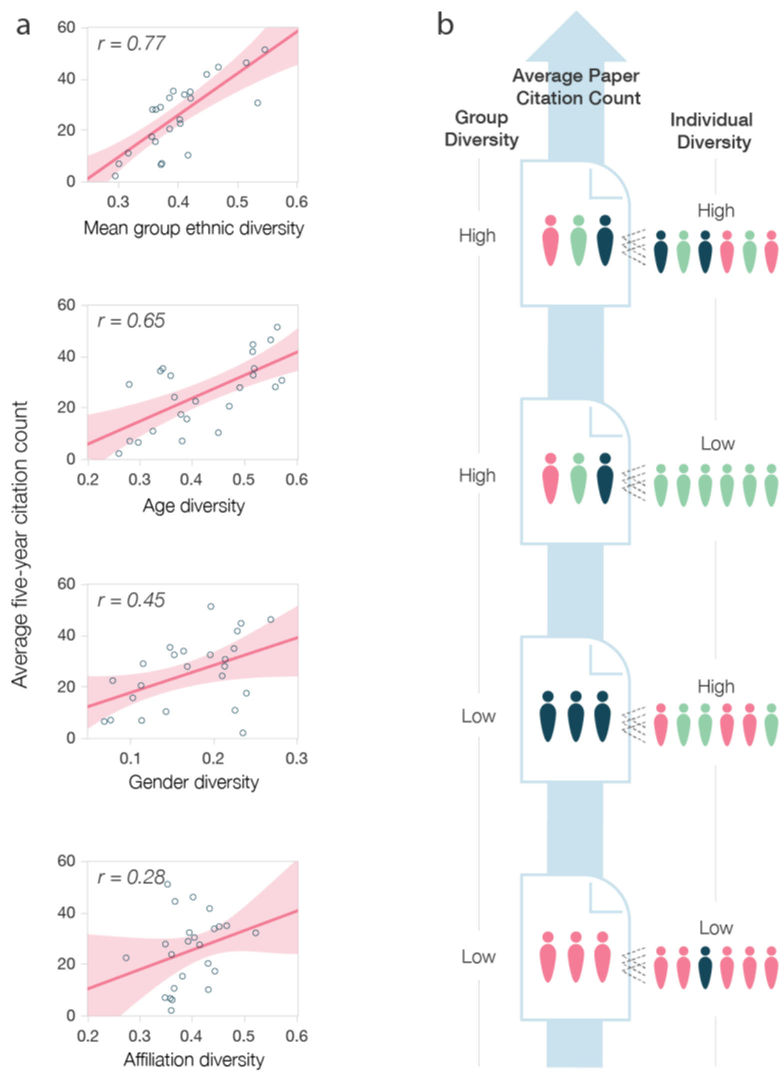


Figure 2.4.1 **Team diversity and scientific impact.** Panel a: an analysis of more than 1 million papers in 24 academic subfields (circles) shows that ethnic diversity correlates more strongly (*r*) with citation counts than do diversity in age, gender or affiliation. Panel b: Comparing team versus individual diversity reveals that diversity within the list of authors on a paper (team diversity) has a stronger effect on citation count than diversity in a researcher's network of collaborators (individual diversity). After Powell [58].

One explanation for this relationship is that scientists who collaborate with a broader variety of colleagues happen to also do better science—that is, the gain could come from having open-minded, collaborative team members, not from ethnic diversity itself. To test this explanation, researchers devised a measure called "individual diversity", which compiled all of an author's earlier coauthors and determined how ethnically diverse that list was. They then compared that to "team" diversity, the degree of ethnic diversity among coauthors of a single particular paper. The results indicate that while both team and individual diversities can be valuable, the former has a greater effect on scientific impact (Fig. 2.4.1 Panel b). In other words, impact is really about how diverse a team is; not how open to diversity each team member is.

Still, the mechanism behind this impact boost remains unclear. It could happen because high-quality researchers tend to attract the best people from around the world, for example, or because different cultures cross-fertilize ideas. Regardless of the underlying mechanisms, these findings suggest that just knowing a team's ethnic diversity can help predict their scientific impact, which in itself has implications [57]. For example, recruiters may want to encourage and promote ethnic diversity, especially if new hires complement the ethnic composition of existing members. Furthermore, while collaborators with different skill sets are often needed to perform complex tasks, these results suggest that multidisciplinarity may be just one of several critical forms of diversity. Bringing together individuals of different ethnicities—with the attendant differences in culture and social perspectives—may also pay off in terms of performance and impact.

Keep in mind, however, that the studies covered in this chapter relied on publication data, meaning that their findings are limited to teams that were *successful enough to publish* in the first place. However, it is possible that a team's diversity can increase its chances of failure in the stages before publication, potentially because of communication and coordination costs or barriers between disciplines. For example, an analysis of more than 500 projects funded by the US National Science Foundation revealed that the most diverse teams are on average the least productive—that is, diversity results in a higher risk of publishing less, or not at all [5, 59]. This highlights a major gap in our understanding of team science in general: We know very little about teams that failed, an issue that we will return to in the outlook chapter (Ch. 4.3).

Therefore, the insights discussed in this chapter should be interpreted under an important condition: when teams *do* form and publish, diversity is associated with a higher impact. Overall, a research team's diversity and breadth of knowledge contribute to the quality of the science that the team produces [55]. Having a diverse team means that collaborators bring different ideas and ways of thinking to the joint effort, improving the outcome of their collaborative work.

Box 2.4.1 Collective Intelligence

The concept of measurable human intelligence, more commonly known as IQ, is based on one remarkable fact: People who do well on one mental task tend to do well on most others, despite large variation in the nature of the tasks [60]. While still considered controversial, the empirical fact of general cognitive ability, first demonstrated by Spearman [61], is now, arguably, the most replicated result in psychology [60]. But if we can accurately measure individual intelligence—and research shows we can—can we gauge the intelligence of a team?

The answer is provided by the concept of collective intelligence [62], referring to the general ability of a group to perform a wide variety of tasks. Interestingly, collective intelligence is not strongly correlated with the average or maximum individual intelligence of the group members. Instead, it's correlated with the average social sensitivity of group members, equality in the distribution of conversational turn-taking, and the proportion of females in the group. Teams with more socially sensitive people, fewer one-sided conversationalists, and more women have been shown to predictably exhibit superior group performance in a variety of tasks. These results suggest that a team's ability to perform well depends primarily on the composition of the team and the way team members interact, rather than the characteristics of individual team members.

2.4.3 Assembling a winning team

How do we assemble a winning team? The most successful teams are embedded in interconnected webs of colleagues from many fields—in other words, a large, wide-ranging network from which to draw ideas. Being part of such networks can offer the kind of inspiration, support, and feedback that leads to the most winning enterprises. But not all networks are equally fertile for collaborations, and some can be less advantageous. The way a team chooses its members plays an important role in how well the team will perform. To see how, let's look at a simple model that aims to capture how teams come together [53, 63].

In any team, there are two types of members: (i) Newcomers, or rookies, who have limited experience and unseasoned skills, but who often bring a refreshing, brash approach to innovation, and (ii) incumbents, the veterans with proven track records, established reputations, and identifiable talents. If we categorize all scientists as either rookies or veterans, we can distinguish four different types of coauthorship links in a joint publication: (1) newcomer-newcomer, (2) newcomer-incumbent, (3) incumbent-incumbent, or, if both are incumbents who have worked together before, (4) repeat incumbent-incumbent.

These four types of links offer a simple way to capture the many possible configurations of diversity and expertise among team members. For example, research on grant-funded projects [59] demonstrates that projects whose principal investigators share prior collaboration experience (a repeat incumbent-incumbent link) are more likely to be successful than those involving members who had never written a joint paper before. However, teams that predominantly consist of repeat incumbent-incumbent links may be limited in their ability to produce innovative ideas because their shared experiences tend to homogenize their pool of knowledge. In contrast, teams with a variety of links may have more diverse perspectives from which to draw but may lack the trust and shared knowledge base needed to make progress.

Varying the proportion of the four types of links within a team can help us understand how certain coauthorship patterns will impact the team's success. We can explore this relationship using two parameters [63]:

- *The incumbency parameter, p,* represents the fraction of incumbents within a team. Higher values of p indicate that a team is mostly made up of experienced veterans, whereas low values of p signal that a team consists mostly of rookies. Therefore, the incumbency parameter approximates the collective experience of a team.
- *The diversity parameter, q,* captures the degree to which veterans involve their former collaborators. An increased q indicates that incumbents are more inclined to collaborate with those whom they have collaborated before.

By varying the two parameters, we can set up a generative model that not only captures teams with different collaborative patterns [63] (see Appendix 1.1 for more details), but also helps us quantify the relationship between the team assembly patterns and innovative output. Indeed, researchers collected the publication records of teams across four different scientific disciplines (social psychology, economics, ecology, and astronomy) and extracted the incumbency and diversity parameters (p and q) by examining how teams were assembled in each case. To measure performance, they compared the values of these parameters with each journal's impact factor, a proxy for the overall quality of the team's output.

Across economics, ecology, and social psychology, there is consistent evidence that a journal's impact factor is positively correlated with the incumbency parameter p, but negatively correlated with the diversity parameter, q. This means that the teams publishing in high-impact journals often have a higher fraction of incumbents. On the other hand, the negative correlation between the journal impact factor and diversity parameter, q, implies that teams suffer when they are composed of incumbents who mainly choose to work with prior collaborators. While these kinds of team alignments may breed familiarity, they do not breed the ingenuity that new team members can offer.

Importantly, this recipe for assembling a successful team is not unique to science—it applies in a broad range of creative enterprises, from Broadway shows to jazz to video games.

- *Musicals*: In a study of 2,258 musicals performed at least once on Broadway between 1877 to 1990 [63], researchers defined a team as the group of individuals responsible for composing the music, writing the libretto and the lyrics, designing the choreography, directing, and producing the show. And although Broadway musicals and scientific collaborations seem like vastly different creative endeavors, they share the same recipe for success. The best-received musicals benefit both from the experience of veterans and the new ideas and fresh thinking of newcomers.
- *Video games*: a study of teams behind 12,422 video games released worldwide from 1979 to 2009 found the most effective collaborations were comprised of people who had experience working together but who brought different knowledge and skills to the task at hand [64]. These findings indicate that prior collaborations and interactions enable groups to avoid intractable conflict, while diverse expertise helps them avoid the pitfalls of groupthink.
- *Jazz*: Data on the entire history of recorded jazz from 1896 to 2010 (175,000 recording sessions) revealed that combining musicians who have worked together with new players is critically important to the success of a jazz album, as measured by the number of times an album is released [65]. That was certainly the case with Miles Davis' "Kind of Blue," the most re-issued jazz album in history. By the time the legendary album was recorded, Paul Chambers, the bass player, was a true veteran who'd played a total of 58 sessions. Out of these sessions, 22 were with Miles Davis, the trumpeter and band leader, and eight were with Wynton Kelly, the pianist. However, Davis and Kelly had never played together prior to the "Kind of Blue" recording sessions. Therefore, while Davis and Kelly were both deeply familiar to Chambers, the fact that they did not know each other added a fresh dynamic to the powerful linkages the incumbent team members already shared, creating a situation ripe for innovation.

Taken together, these results show that there's a strong correlation between team composition and the quality of the work they produce. In particular, these findings teach us two important lessons about how to assemble a successful team [53]. First and foremost, experience matters: While brash newcomers may brim with energy and are fearless in taking risks, teams composed entirely of rookies are more likely to flop. Second, although the experience of veteran scientists is important, successful teams include some portion of new people who can stimulate new ideas and approaches. Too many incumbents, especially those who have worked together repeatedly in the past, limit diverse thinking, which can lead to low-impact research.

2.4.4 The Dynamic Duos

If team success depends on the balance of new collaborators and existing ones, how do scientists typically engage with their co-authors? Do we tend to gravitate towards a few very close collaborators, or do scientific collaborations feature a high turnover rate? An empirical analysis of 473 researchers from cell biology and physics and their 166,000 collaborators [66] reveals three important patterns in the way we form and maintain collaborations.

First, scientific collaborations are characterized by a high turnover rate, dominated by weak ties that do not last. Indeed, out of the more than 166,000 collaboration ties, 60–80% lasted for only a single year. And even when a relationship lasted more than two years, it didn't have much long-term staying power: Roughly two-thirds of collaborators went their separate ways within five years.

Second, whereas weak ties dominate most collaborations, "super-ties"—extremely close working relationships—are not uncommon. Nine percent of biologists and 20% of physicists have a super-tie collaborator with whom they coauthored more than half of their papers. In particular, 1% of collaborations lasted more than 20 years. These capture lifelong collaborative partners—they are the Batmen and Robins of science. When we quantify the frequency of super ties [66], we find that they occur every 1 in 25 collaborators on average.

Third, and most important, super ties yield substantial productivity and citation premiums [66, 67]. If we compare the papers a scientist published with her super-tie to those she published with other collaborators, her *productivity with the super tie was roughly 8 times higher*. Similarly, the additional citation impact from each super tie is 14 times larger than the net citation impact from all other collaborators. For both biology and physics, publications with super-ties receive roughly 17% more citations than their counterparts. In other words, the work you do with your super-tie, if you have one, is what tends to define your career.

The significant positive impact of super-ties reflects the fact that "life partners" in science exist for a reason. For example, researchers analyzed collaboration records among 3,052 Stanford University faculty between 1993 and 2007, extracting data from student dissertation records, grant proposal submissions, and joint publications [67]. They identified when new, untenured faculty arrived on campus, tracing when these newcomers began to form their first ties and exploring why some of these relationships persisted over time, becoming repeat collaborations. They found that repeated collaborations are of a fundamentally different nature from first-time collaborations—whereas new collaborations are mostly driven by opportunity and preference, repeated collaborations are a function of obligation and complementary experience. Indeed, when someone seeks a collaborator for the first time, they tend to select someone who has a similar skill-set, as they are less familiar with the other person's workstyle. Yet, as the two worked together on more projects, they become better acquainted with each other's unique talents. If they decide to continue collaborating, it suggests that each individual has realized that their partner has something novel to contribute, which may lead to a better final outcome. Thus, productive relationships are most often sustained when the individuals have non-identical knowledge, so they can be complementary to each other.

The value of a super tie is exemplified by the case of Michael S. Brown and Joseph L. Goldstein. Professors at the University of Texas Southwestern Medical School, Brown and Goldstein have both enjoyed stellar careers and achieved remarkable productivity, each publishing over 500 papers and earning numerous awards, including the Nobel Prize and National Medal of Science. Yet a quick look at their publication records reveals a truly special relationship: More than 95% of their papers are jointly authored. Searching through the Web of Science databases, we find that Brown and Goldstein have coauthored a stunning 509 papers by 2018. Over the course of their long careers, Goldstein has published only 22 papers without Brown, and Brown has published only four papers without Goldstein.

The impact of their joint research goes way beyond their academic accolades. The duo has made real impact in improving human health. In a joint paper published in 1974, Brown and Goldstein discovered LDL (low-density lipoprotein) receptors, which earned them a Nobel Prize in Physiology or Medicine in 1985 [68]. LDL, which is often referred to as the "bad cholesterol," is highly associated with cardiovascular diseases like coronary artery disease, the number one killer of people worldwide [69]. Drugs that help lower cholesterol levels, called statins, are more widely prescribed than any other type of medication. Atorvastatin, the most popular variant of statins (marketed under the brand name Lipitor) is the world's best-selling drug of all time, with more than $125 billion in sales over its 14-year life-span. It's not a stretch to say, then, that millions of lives have been saved thanks to Brown and Goldstein's super-tie.

Chapter 2.5

Small and large teams

In 2015, *Physical Review Letters* (*PRL*), one of the most prestigious publication venues for physicists, published a highly unusual paper [70]. *PRL*'s stated goal is to offer a venue for rapid communication of important results—hence each paper has traditionally been a short 'letter' limited to four pages in length. The 2015 paper, on the other hand, was a record-breaking 33 pages long. Yet only nine pages featured the research itself; the remaining 24 were used to list the authors and their institutions. This high-energy physics paper was the first joint paper produced by the teams that operate ATLAS and CMS, two massive projects conducted using the Large Hadron Collider (LHC) at CERN, Europe's particle-physics lab near Geneva, Switzerland. Together, an astonishing 5,154 authors contributed to the discovery, representing the largest number of contributors to a single research article in history [71].

One of the most profound shifts in science and technology today is the shift toward larger and larger teams across all fields of science. In 1955, the average team size in science and engineering was around 1.9, indicating that two-person partnerships were the norm for collaborative work. This number nearly doubled over the next 45 years, corresponding to the 17% growth in team size per decade [2, 11] (Fig. 2.5.1). And this growth continues even today: While in 2000 a typical paper had 3.5 authors, by 2013 that number had grown to 5.24. Similar (though less dramatic) growth has occurred in the social sciences: The average social science paper today is written by a pair of authors rather than solo authors, with the number of collaborators continuing to grow every year. Even in the arts and humanities, where over 90% of papers are still single authored, there is also a significant, positive trend toward team-authored papers ($P < 0.001$).

Furthermore, increases in team size are not unique to academia, but apply to other creative work as well. For example, in the US, the average number of inventors on patent applications has risen from 1.7 to 2.3, with the number continuing to grow every year.

This trend is about more than just simple growth. As we will see in this chapter, it reflects a tectonic shift in the ways that scientists work and teams organize themselves. And that change has tremendous consequences for the future of science, since large and small teams produce fundamentally different, though equally valuable, types of research. Indeed, with the growth of teams comes a challenge for the scientific community: If scientists and funding agencies do not make a conscious effort to maintain small teams, these scrappy, free-thinking units could soon disappear, their unique contributions vanishing along with them.

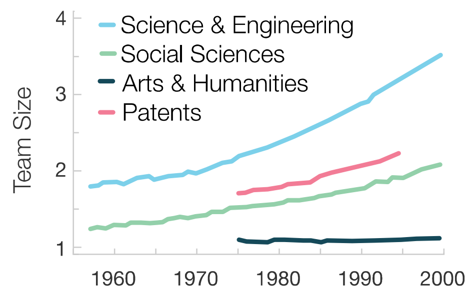


Figure 2.5.1 **The growing size of teams.** Each line represents the arithmetic average of team size taken over all subfields in each year. After Wuchty *et al.* [2].

2.5.1 Not simply a change in size

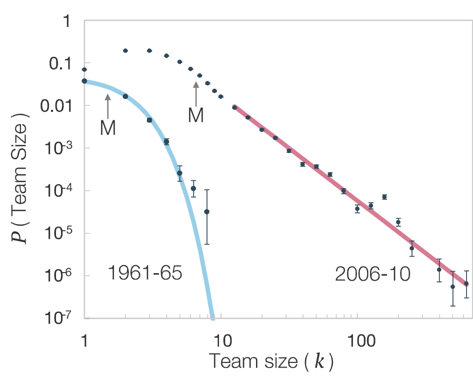


Figure 2.5.2 **Fundamental changes in team structure.** The team size distribution between 1961 and 1965 is well described by a Poisson distribution (blue curve). In contrast, the 2006– 2010 distribution features an extensive power-law tail (red line). The arrows mark the mean values of each distribution. Error bars correspond to one standard deviation. After Milojević [72].

The shift toward larger teams in science reflects a fundamental change in team composition [72]. Fig. 2.5.2 compares the distributions of team size in astronomy in two periods: 1961–1965 and 2006–2010. The average team size in astronomy grew from 1.5 to 6.7 between these two periods (see the arrows in Fig. 2.5.2). Yet the 2006–2010 team size distribution is not simply a scaled-up version of the 1961–1965 distribution. Rather, the two distributions have fundamentally different shapes. In the 1961–1965 period, the number of papers decays rapidly as the team size increases. Not only is the average team size small, but we find not a single paper with more than eight authors. Indeed, the team sizes in 1960s are best approximated with an exponential distribution (blue curve in Fig. 2.5.2), meaning that most teams have sizes within close vicinity of the average, and that there are no outliers.

Yet, after 45 years, the distribution has changed dramatically, and now features a prominent tail, consisting of mega-teams with several hundred authors. Unlike in the 1960s, the tail of this more recent distribution is well approximated by a power law function (red line in Fig. 2.5.2). This shift from an exponential to a power law distribution implies that the increase in a team's size is more complicated than it may seem. Indeed, these two mathematical functions indicate that two fundamentally different modes characterize the process of team formation.

The first and more basic mode leads to the creation of relatively small "core" teams. In this mode, new members join the team with no regard for who is currently on the team. Core teams thus form by a purely random process and thus produce a Poisson distribution of team sizes, making large teams exceedingly rare. As such, the distribution is best depicted with an exponential function. This mode was likely the status quo in astronomy until the 1960s.

The second mode produces "extended" teams. These start as core teams but accumulate new members in proportion to the productivity of their existing members—a "rich-get-richer" process. As such, a team's current size determines its ability to attract new members. Given time, this mode gives rise to a power-law distribution of team sizes, resulting in the large teams with 10-1,000 members that we observe in many fields today.

A model of team formation based on core and extended teams can accurately reproduce both the empirically observed team size distributions and their evolution over time in many fields [72]. Most important, by fitting the model to a particular discipline across several different eras, it allows us to assess how the two modes of team formation have affected knowledge production. Interestingly, the results indicate that the fraction of articles produced by core and extended teams has remained roughly constant over time. This means the increase of team size is not because larger teams have replaced the smaller core teams. Rather, we observe a growth in both types of teams—a gradual expansion of core teams and a faster expansion of extended teams.

These changes in team formation may also have consequences for a team's longevity, as team size may be a crucial determinant of survival [34]. Research on the lifetime of collaborative teams shows that large teams tend to persist for longer if they dynamically alter their membership, as changing their composition over time increases their adaptability. On the other hand, small teams tend to be more stable over time if their membership remains more stable; a small team with high turnover among its members tends to die out quickly.

So far, we've demonstrated that in science, teams are growing in size, hence innovation increasingly happens in team settings. Is that a good thing for scientists—and for the creation of knowledge in general?

2.5.2 Team size: Is bigger always better?

The LIGO experiment, which offered the first evidence of gravitational waves, was called the "discovery of the 21st century," and recognized by the Nobel prize within two years of discovery. This experiment—the collective work of more than a thousand researchers—is a testament to the power of large teams in tackling the 21st century's toughest challenges. Indeed, one could argue that the shift toward large teams fulfills an essential function: Since the problems of modern society are increasingly complex, solving them requires large, interdisciplinary teams [7–10] that combine their members' talents to form an enormous and varied pool of expertise. Furthermore, the LIGO experiment exemplifies the kind of achievement that simply is not feasible for smaller groups to pull off. The project required unprecedented technology, and thus demanded unprecedented material and personnel resources. It is no surprise that the paper reporting the discovery listed more than 1,000 researchers.

The universal shift toward larger and larger teams across science and technology suggests that large teams, which bring more brain-power and diverse perspectives, will be the engines for tomorrow's largest advances. Research has consistently shown that as teams become larger, their products—be they scientific papers or patented inventions—are associated with higher citation counts [2, 73]. These trends seem to offer a simple prescription for the future of science: bigger is always better.

Yet there are reasons to believe that large teams are not optimal for all tasks. For example, large teams are more likely to have coordination and communication issues—getting everyone onboard to try out an unconventional hypothesis or method, or convincing hundreds of free-thinking individuals to change direction at once, is often challenging. Psychology research shows that individuals in large groups think and act differently. They generate fewer ideas [74, 75], recall less learned information [76], reject external perspectives more often [77], and tend to neutralize one another's viewpoints [78]. Large teams can also be risk-averse, since they have to produce a continuous stream of success to "pay the bills" [79].

All of which raises the question of whether relying on large teams is truly a one-size-fits-all strategy for producing groundbreaking science. Indeed, new evidence suggests that team size fundamentally dictates the nature of work a team is capable of producing, and that smaller team size confers certain critical benefits that large teams don't enjoy.

2.5.3 Large teams develop science; small teams disrupt it.

To understand how team size may affect the nature of the science and technology they produce, let's consider two examples. In Fig. 2.5.3, we pick two well-known papers with similar impacts, but which contribute to science in very different ways. The Bak, Tang and Wiesenfeld (BTW) article on self-organized criticality [80] received a similar number of citations to the Davis *et al.* article on Bose-Einstein condensation [81]. Yet the Bak *et al.* paper was groundbreaking in a way that the Davis *et al.* paper was not. Indeed, most research following upon Bak *et al* cited the BTW paper only, without mentioning its references (green links in Fig. 2.5.3a). By contrast, Davis *et al*, for which Wolfgang Ketterle was awarded the 2001 Nobel Prize in Physics, is almost always co-cited with the papers the Davis *et al* paper itself cites (brown links in Fig. 2.5.3a).

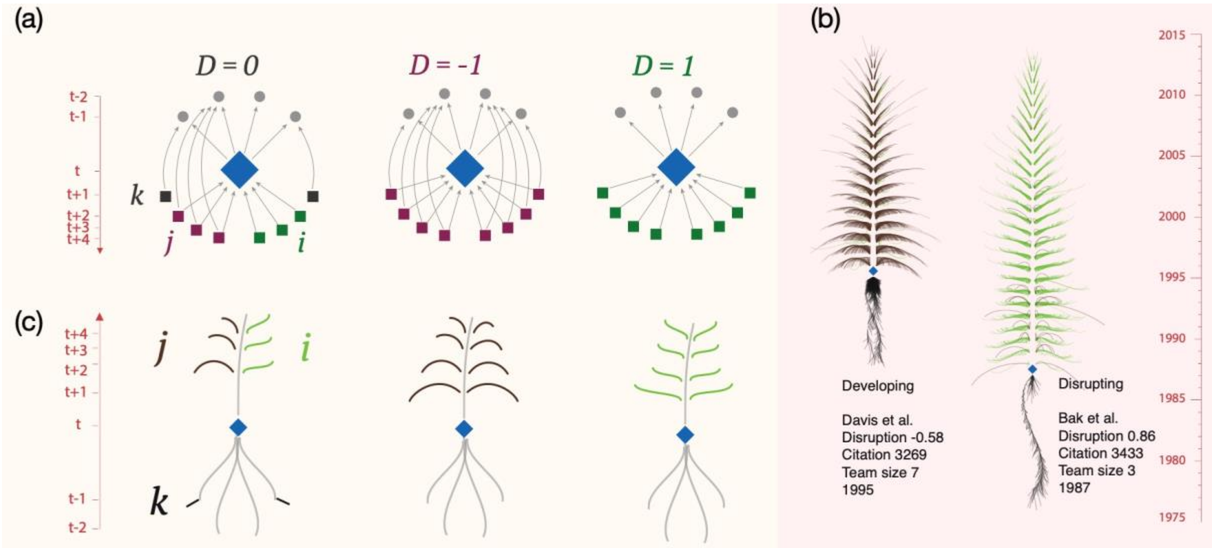


Figure 2.5.3 **Quantifying disruption. a,** Citation network depicting a paper (blue diamond), its references (gray circles), and subsequent works (rectangles). Subsequent works may cite: (1) only the focal work (*i*, green), (2) only its references (*k*, black), or (3) both the focal work and its references (*j*, brown). Disruption of the focal paper is suggests that a paper may either balance disruption and development (*Disruption* = 0), primarily broadcast the importance of prior work (*Disruption* = -1), or completely overshadow prior work by receiving all subsequent attention itself (*Disruption* = 1). **b,** Citation tree visualization that illustrates how a focal paper draws on past work and passes ideas onto future work. "Roots" are references cited by the focal work, with depth scaled to their publication date; "branches" on the tree are citing articles, with height scaled to publication date and length scaled to their number of future citations. Branches curve downward (brown) if citing articles also cite the focal paper's references, and upward (green) if they ignore them. **c**, Two articles of similar impact are represented as citation trees, "Bose-Einstein Condensation in a Gas of Sodium Atoms" by Davis et al., and "Self-organized criticality: An explanation of the 1/f noise" by Bak et al. After Wu et al. [82].

The difference between the two papers is not reflected in citation counts, but in whether they develop or disrupt existing ideas—i.e. whether they solve an established scientific problem or raise novel questions. "Developmental" projects, those that build upon earlier research, seek to advance understanding of an existing problem, hence they tend to be cited along with earlier work, like the Davis *et al* paper. "Disruptive" projects, on the other hand, tend to establish a brand new frontier of inquiry, hence they are more likely to be cited without the predecessors, since they represent a departure from previous knowledge.

So, do large or small teams create the more disruptive work?

To quantify the degree to which a work amplifies or eclipses the prior art it draws upon, we use a disruption index *D*, which varies between -1 (develops) and 1 (disrupts) [83]. For example, the BTW model paper has a disruption index of 0.86, indicating that most of the papers that cite it, do so by citing the BTW paper alone, ignoring the work that the BTW paper built upon. By contrast, the Davis. *et al* paper has a *D*=-

0.58, indicating that it is frequently co-cited with its predecessors. This reflects the fact that the BTW model launched entirely new streams of research, whereas Davis *et al*'s experimental realization of Bose-Einstein condensation, while a Nobel-worthy effort, primarily elaborated on possibilities that had already been posed elsewhere.

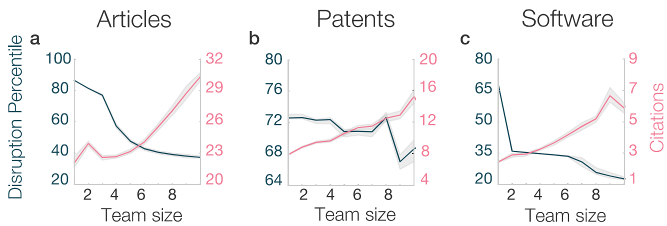


Figure 2.5.4 **Small teams disrupt, big teams develop.** To examine the relationship between team size and disruption, we collected data from three domains: (1) the Web of Science database, containing articles and the papers they cite; (2) patents granted by the USPTO and their citations; (3) software projects on GitHub, a web platform that allows users to collaborate on software and "cite" other repositories by building on their code. For research articles (a), patents (b), and software (c), median citations (red curves indexed by the right y-axis) increase with team size, whereas average disruption percentile (green curves indexed by the left y-axis) decreases with it. After Wu *et al*. [82].

Our analysis shows that over the past 60 years, larger teams have produced research articles, patents, and software products that garner higher impact than smaller teams. Yet, interestingly, their disruptiveness dramatically and monotonically declines with each additional team member (Fig. 2.5.4). Specifically, as teams grow from 1 to 50 members, the disruptive nature of their papers, patents, and products drops by 70, 30 and 50 percentiles, respectively. These results indicate that large teams are better at further developing existing science and technology, while small teams disrupt science by suggesting new problems and opening up novel opportunities.

But is the observed difference in the work produced by large and small teams really due to team size? Or can it be attributed to differences in other confounding factors? For example, perhaps small teams generate more theoretical innovations, which tend to be more disruptive, and large teams generate more empirical analyses, which are more likely to be developmental. Or, maybe there are differences in the topics that small and large teams tend to tackle. Another possibility: Perhaps certain types of people are more likely to work for smaller or larger teams, thus changing the outcomes associated with each.

Luckily, we can control for each of these plausible factors, finding that the effect of team size appears to arise as a result of team dynamics, rather than because of qualitative differences between individuals in different-sized teams. Differences in topic and research design may only account for a small part of the relationship between team size and disruption. Most of the effect (66% of the variation) indeed appears to be a function of team size.

Do large and small teams turn to different sources when conducting research? To answer this question, we measured how deeply small and large teams build on past literature by calculating the average age of references cited. We find that solo and small teams were much more likely to build on older, less popular ideas. This is likely not a function of knowledge: Since larger teams have more members, their expertise spans a broad range of subjects; as such, their members were probably just as aware of older, less known work as the scientists who work within small teams. However, large-team scientists tend to source their ideas from more recent, and higher-impact, work. Consequently, large teams receive citations quickly, as their work is immediately relevant to contemporaries. By contrast, smaller teams experience a much longer citation delay, but their work tends to persist further into the future, achieving a more enduring legacy.

2.5.4 Science needs both large and small teams

Together, the results in the last section demonstrate that small teams disrupt science and technology by exploring and amplifying promising ideas from older and less popular work, whereas large teams build on more recent results by solving acknowledged problems and refining existing designs. Therefore *both* small and large teams are crucial to a healthy scientific ecosystem.

Large teams remain as an important problem-solving engine for driving scientific and technological advances, especially well-equipped to conduct large-scale work in personnel- and resource-intensive areas. The LIGO experiment, for example, was a feat that no small team could have achieved and has opened up a new spectrum of astronomical observation. But, while the successful detection of gravitational waves required a large and diverse team, it is also important to note that the theoretical framework that LIGO was designed to test was proposed by a single individual [84]. One kind of team was required to propose the concept of gravitational waves, and a very different kind of team was required to detect them. Both endeavors moved science forward, but in very different ways.

What do these results mean for us, scientists? When putting together a team to tackle a particular challenge, we may want to first consider the goals of the project. Small teams are more agile, and better positioned to test a novel or disruptive idea. This means one is better off starting with a smaller team in the proof-of-concept phase and engage the larger team later to fulfill the idea's promise. For scientists, it may be easy to believe that adding another member or three to a team will always be the right choice, or at the very least can't hurt. But as the findings in this chapter show, when trying to develop innovative ideas, more people isn't always better, as larger teams shift the focus and outcome away from disruption.

It is also important to think carefully about funding decisions in light of these findings. Naturally, we can count on large teams to reliably produce important work. Yet we can't assume that the bigger the team, the better its contribution will be. There is evidence that funding agencies may prefer larger teams over smaller ones, even when both are equally qualified [85]. This tendency can contribute to a self-fulfilling prophecy, funneling support disproportionately to large teams, and promoting a scientific world wherein those that master highly collaborative work have a crucial advantage.

However, as this chapter shows, there is a key role in science for bold solo investigators and small teams, who tend to generate new, disruptive ideas, relying on deeper and wider reach into the knowledge base. Hence, as large teams flourish in an environment historically populated with small teams and solo investigators, it is crucial to realize that this shift also implies that there are now fewer and fewer small teams. If this trend continues, the scientific community may one day find itself without the scrappy, outside-the-box thinkers who supply large teams with grandiose problems to solve.

Chapter 2.6

Scientific Credit

At the Nobel Prize banquet in December 2008, Douglas Prasher, dressed in a white tie and tails, sat with his wife, Gina, beneath glittering chandeliers suspended from the Blue Hall's seven-story ceiling. Prasher was in Stockholm to celebrate the impact his work has had on the world: GFP, the luminous protein that Prasher had cloned for the first time in 1992, had become "a guiding star for biochemistry," according to the Nobel Foundation, allowing scientists to glimpse the inner workings of cells and organs in unprecedented detail.

However, Prasher was attending the banquet as a *guest*, not a prizewinner. Among the honorees that night, the celebrated winners of the 2008 Nobel Prize in Chemistry, were Martin Chalfie and Roger Tsien, two researchers to whom Prasher had mailed his cloned GFP gene in a moment of career-crushing despondency just when he decided to leave science. On the morning of October 8, 2008, when Prasher heard on his kitchen radio the news that GFP-related research had won the Nobel prize, he was just getting ready to go to work—not in a lab or university, but as a courtesy van driver at a Toyota dealership in Huntsville, Alabama. Prasher's trip to Sweden, paid for by the newly minted prizewinners, was the first vacation he had taken in years. The tuxedo he wore was rented for the night, and it paired well with the dressy shoes that a Huntsville store had let him borrow. He watched the ceremony from the audience because his decision to leave science decades ago also dropped him off the Nobel Committee's map.

In this and the next chapters, we are going to focus on a question of utmost importance today: How is scientific credit allocated? Indeed, for the solo-authored work that dominated previous eras, there was no ambiguity as to where the credit should go. But since modern discoveries are increasingly made by teams, involving anywhere between two and a *thousand* authors, who should we attribute the credit to? Or perhaps the more pragmatic question isn't who *should* get the credit, but who *will* get the credit? In this chapter, we will examine the first question; in the next chapter, we will address the second.

For many, discussions about credit are unnerving, even taboo. Indeed, we do science for the sake of science, not to revel in the glory of recognition. But, whether we like it or not, credit is allocated unevenly, so it is important to understand how this process works, if not for ourselves, then for our students and collaborators. Especially now that we have learned so much about team science, we wouldn't want the issue of credit to stand in the way of very valuable collaborations. While none of us want to claim credit that doesn't belong to us, we also don't want to find ourselves in Douglas Prasher's borrowed shoes at the Nobel Prize banquet, clapping along in stunned disbelief while someone else accepts the trophy for his work.

2.6.1 Who did what in a paper?

Compared with other professions, science is notorious for its emphasis on celebrating individuals rather than teams, particularly when it comes to rewards and recognition [12]. Indeed, iconic achievements are often known by the discovering scientist's name: Euclidean geometry, Newton's laws of motion, Mendelian inheritance, and the Heisenberg uncertainty principle, to name a few. Similarly, the science prizes that bestow significant financial reward and notoriety—from the Nobel Prizes, to the Fields Medal, to the A.M. Turing Award—tend to exclusively value individual contributions.

While the mode of production in science has been shifting toward teams, important decisions in science are still based almost entirely on individual achievement. Indeed, appointment, promotion, and tenure processes in academia center on individual evaluations, despite the fact that most careers are now built through teamwork. We scientists therefore often need to distinguish our contributions from our collaborators', whether applying for a grant, being considered for an award, seeking an academic appointment, or requesting a promotion. So how do tenure committees and award-granting institutions attempt to discern which individuals deserve credit for collaborative research?

The difficulty with allocating credit for collaborative work is rooted in a deep information asymmetry: We cannot easily discern the significance of individual contributions by reading the byline of a paper. For example, Fig. 2.6.1 shows three Nobel prize winning papers with multiple authors, each published in the same journal, *Physical Review Letters* (*PRL*). Only one author from each paper was awarded the Nobel prize. So, who were the lucky prizewinners? As the figure shows, there is no simple answer: the Nobelist is sometimes the first author, sometimes the last, or can be somewhere in between.

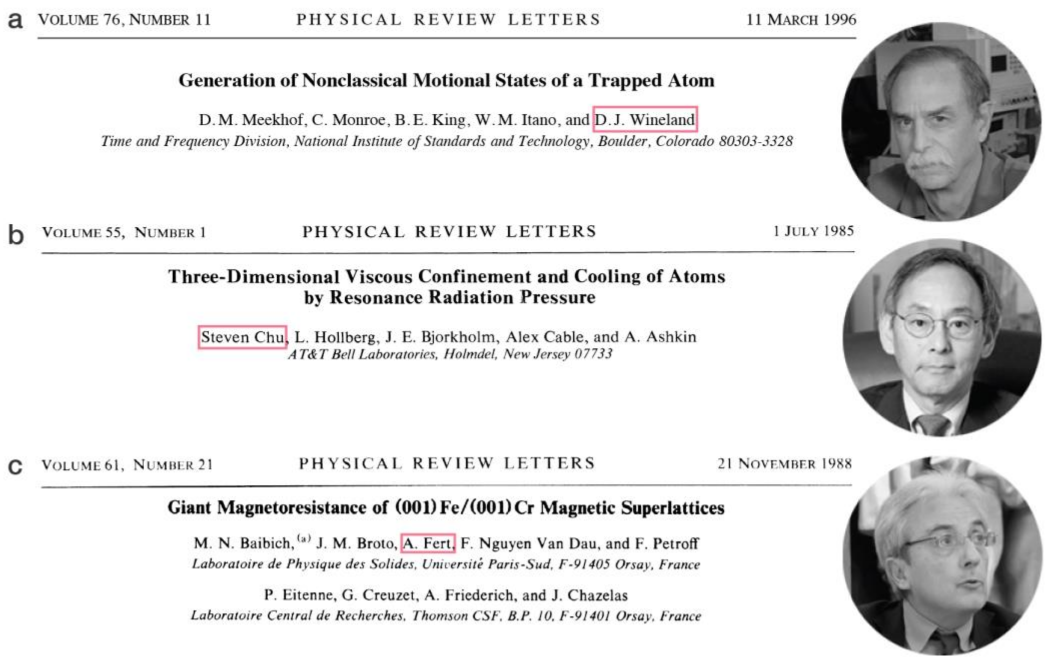


Figure 2.6.1 **Who gets the Nobel?** (A) The last author, David J. Wineland was awarded the 2012 Nobel Prize in Physics for his contribution to quantum computing. (B) Steven Chu, the first author, won the 1997 Nobel in Physics for the paper focusing on the cooling and trapping of atoms with laser light. (C) In 2007, Albert Fert, the middle author of the paper, received the Nobel Prize in Physics for the discovery of the giant magnetoresistance effect (GMR). All three examples are prize-winning papers published in the same journal, *Physical Review Letters*, demonstrating the ambiguity of allocating credit by simply reading the byline of a paper.

To be clear, this issue isn't just about recognition, or giving credit where credit is due; it's also about responsibility—because with greater contribution comes greater responsibility. Who is responsible for which part of the project? Lacking consistent guidelines for classifying individual contributions to a paper, we rely on our own assumptions, traditions, and heuristics to infer responsibility and credit. The most commonly used method is by inspecting the order of authors on a paper [86, 87]. In general, there are two norms for sorting authors, alphabetical and non-alphabetical. Let's start with the more prevalent one: non-alphabetical ordering.

2.6.2 The first or the last

In many areas of science, especially the natural sciences, authors order themselves on a byline based on their contributions within the team. In biology, the individual performing the lion's share of the work is the lead author, followed sequentially by those making progressively lesser contributions. Therefore, we expect that the second author had less substantial contributions than the first, but more than the third author, and so on. The critical exception is the last author, who often gets as much credit, if not more, than the first author. Listing the principal investigator last has become an accepted standard in natural sciences and engineering. The last author, also called the corresponding author, is assumed to be the intellectual, financial, and organizational driving force behind the research. Hence evaluation committees and funding bodies often take last authorship as a sign of intellectual leadership and use this as a criterion in hiring, granting, and promotion.

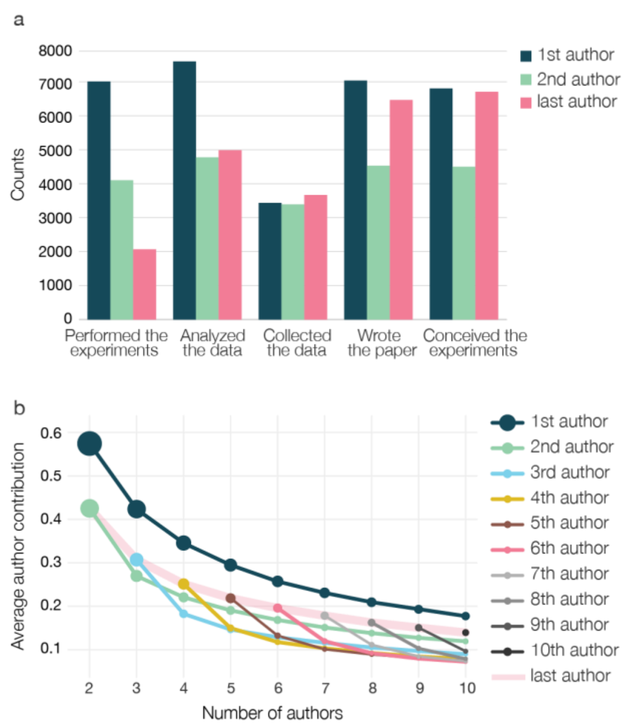


Figure 2.6.2 **Author contributions in a paper.** (a) Authors of different ranks make different contributions to the paper; (b) Average number of distinct contributions by an author as a function of its ranking, confirming that the first and last authors contributed most to the paper. After Corrêa *et al.* [88].

But does the order of authorship indeed reflect what it purports to represent? We now have quantitative answers to this question, thanks to specific author contribution sections included in publications across multiple disciplines [88-90]. *Nature*, for example, started to include explicit lists of author contributions in 1999 [91], a practice now adopted by many other journals. While the exact classification scheme differs from journal to journal, authors are generally asked to self-report their contributions in six categories: (1) analyzed data, (2) collected data, (3) conceived experiments, (4) performed experiments, (5) wrote the paper, and (6) revised the paper. Analyzing these self-reports allows us to relate the duties performed on any given project to author order. Indeed, by analyzing about 80,000 articles published between 2006 and 2014 in the multi-disciplinary journal *PLoS ONE*, researchers confirmed that first and last authors are indeed the two most important on a paper: the first author is typically involved in almost all aspects of the reported research, from running the experiment to writing the paper, and the last author assumes a supervisory role for the project, mainly designing and conceiving the research and writing the paper (Fig. 2.6.1A). Regardless of how many authors are on the paper, the first author always makes the largest number of contributions, and the last author usually contributes the second most (Fig. 2.6.1B). Interestingly, however, only the first and the last authors stand out—followed by the second author but with almost no detectable difference in contributions for all other authors on the paper. The contributions by the third and fourth author, for instance, are typically indistinguishable (Fig. 2.6.1B).

These results suggest that author positions in the byline do offer an effective way to infer each team member's true contributions. But, there are caveats. First, the way that journals collect this information is not exact. Since there is no clear definition of each contribution, just general criteria, authors may have their own interpretations about what "analyzed data" or "conceived experiments" means. And it seems that, at times, coauthors do not necessarily agree amongst themselves about who contributed what. For example, in a study of all manuscripts submitted to the *Croatian Medical Journal*, researchers compared which contributions the corresponding author credited to their coauthors versus which contributions those authors claimed for themselves. They found that more than two thirds (69.4%) of 919 corresponding authors disagreed with their coauthors regarding contributions [92]; specifically, coauthors listed more contribution categories on their own forms than the corresponding authors chose for them.

Second, the practice of listing authors based on their contributions is not always exercised [87]. Sociology and psychology, for example, do not follow the tradition of putting the most senior author last. In these disciplines, being the last author really *is* the least desirable position. Moreover, it is not uncommon for a mentor to be in the first-author slot for the crucial guidance, intellectual contributions, and financial leadership of the project, even if the trainee may have done all the heavy lifting.

The uneven acceptance of senior authorship often leads to ambiguities when evaluating a scientist, especially when it comes to cross-disciplinary hires. A psychology professor may ask why a prospective applicant from another discipline doesn't have any recent first-author publications, since in psychology, the absence of first-authorship is something to be frowned upon, even for an established scientist. But since listing senior authors last is the norm in other fields, like biology and physics, a biologist or physicist may see too many first-author papers as a red flag, calling into question the candidate's collaboration style and mentorship abilities.

The different preferences on author ordering also sometimes lead to conflicts. For example, a 2017 paper published in *Genes, Brain, and Behavior* [93] was retracted a few months after its publication, but not for academic misconduct or error, but due to a dispute over the order of the authors, prompting the journal to release an unusual statement:

"*The retraction has been agreed as all authors cannot agree on a revised author order, and at least one author continues to dispute the original order.*"

Joint First Authorship.

The percentage of publications in which two or more coauthors claim joint first authorship has dramatically increased in the past 30 years. Such "co-first authorship," as it's called, is particularly prominent in biomedical and clinical journals. Many journals went from having no such papers in 1990 to having co-first authorship in more than 30% of all research publications in 2012 [94].The increase has been most dramatic in high-impact journals: In 2012, 36.9% of *Cell* papers, 32.9% of *Nature* papers, and 24.9% of *Science* papers had co-first authors.

There are many reasons for the increasing prevalence of joint first authorships. First, publishing in a competitive journal requires extensive effort by more than one lead investigator. Hence this trend is likely to continue, especially as research grows increasingly complex and as teams are increasingly needed to tackle important scientific and clinical challenges. Also, in interdisciplinary work, a project often requires the joint, focused contribution of two or more lead authors with complementary expertise; no one individual has all of the knowledge needed to usher a project through independently.

Yet, co-first authorships also introduce new credit allocation problems. Indeed, although co-first authorship is clearly indicated by asterisks or superscripts in the original paper, when a citation is encountered on a reference list, there is no way of knowing whether it was a co-first author situation or not. Worse still, for long author lists, citations adopt the "*et al*" style, which lists the first author's last name only. At the time of this writing, we are only just beginning to develop new conventions around joint authorships: journals like *Gastroenterology* [95, 96] and *Molecular Biology of the Cell* [97], for instance, now require authors to use bold lettering in citations referring to joint first authorships, so that every deserving author receives equal recognition every time their work is cited.

2.6.3 From A to Z

While biology or medicine place special emphasis on first and last authors, disciplines like mathematics and experimental particle physics are known for their stubbornly alphabetical approach to author lists. Yet when researchers estimated alphabetical authorship across all fields of science, they found that the overall use of the practice is on the decline [98]. In 2011, less than 4% of all papers chose to list their authors alphabetically. Admittedly, 4% is a small number, but that does not mean that alphabetical authorship is likely to disappear entirely. The decline simply reflects the fact that non-alphabetical disciplines, like biology and medicine, are expanding more rapidly than fields like mathematics. Indeed, the alphabetic convention remains highly concentrated in a handful of scientific subjects, within which its use has remained rather stable. Alphabetic listing of authorship is most common in mathematics, accounting for 73.3% of papers (Table 1.1). Finance comes in second with 68.3%, followed by economics and particle physics.

Subject Category	Alphabetical Percentage
Biochemistry & Molecular Biology	-0.1%
Biology	0.2%
Medicine, General & Internal	0.2%
Materials Science, Multidisciplinary	0.6%
Neurosciences	0.8%
Chemistry, Multidisciplinary	0.9%
Chemistry, Physical	0.9%
Physics, Applied	1.3%
Engineering, Electrical & Electronic	3.6%
History	30.7%
Physics, Mathematical	32.1%
Statistics & Probability	33.8%
Mathematics, Applied	44.7%
Economics	57.4%
Physics, Particles & Fields	57.4%

Mathematics	72.8%	

Table 1.1: **The prevalence of alphabetical ordering of authors**. The table shows the fraction of "alphabetical" papers in a given subject, listing a selection of subjects that have a low, mid, or high fraction of intentionally alphabetical papers. After Waltman [98].

Why don't these fields embrace a more informative non-alphabetical convention? A statement from the American Mathematical Society (AMS) offers a hint [42]:

> "In most areas of mathematics, joint research is a sharing of ideas and skills that cannot be attributed to the individuals separately. Researchers' roles are seldom differentiated (as they are in laboratory sciences, for example). Determining which person contributed which ideas is often meaningless because the ideas grow from complex discussions among all partners."

Additionally, in fields that obey alphabetical ordering, the definition of authorship is substantially different from those that don't. In non-alphabetical disciplines, since the placement of names within the author list clearly suggests the role they played in the project, individuals who made a marginal contribution to the work can be added to the author list in a way that does not devalue the core authors' hard work. But since everyone on an alphabetical list is considered equal, adding an undeserving person is far more costly, and hence warrants more delicate considerations. For example, in alphabetical fields like economics, merely contributing data to a project doesn't warrant authorship, while in biology or medicine, which are non-alphabetical disciplines, it does. Consequently, the acknowledgments section on a mathematics paper often contain acknowledgements for significant "author-worthy" contributions, like providing the foundational idea for the project or correct proofs of key technical results needed by the authors. It is not uncommon for mathematicians to offer their colleagues authorship, only to be politely declined. So colleagues whose contributions were essential to the success of a paper end up merely acknowledged.

There are several benefits to the alphabetical ordering. For starters, it's convenient, allowing authors to avoid the awkward debate about whose name goes first or second. Furthermore, with the bar for authorship held high, alphabetization decreases the frequency of "guest" authors. (See Box 2.6.1)

Yet, alphabetical ranking also leaves out important information. Even if all authors have contributed equally, there is plenty of room, without explicit attribution, for the community to make (often inaccurate) inferences about who a paper's rightful "owner" is. As we will see next, this can have some serious consequences.

Box 2.6.1 Ghosts and Guests

The trend of growing author lists has a troubling side effect: the rise of "guest authors," those who made only very minimal contributions to the research. How common are these guest authors? A recent survey of 2,300 lead authors found that a shocking 33% of scholarly papers in the biological, physical or social sciences had at least one author whose contribution did not meet accepted definitions for co-authorship [42, 99]. Survey results indicate that the incidence of "undeserved" coauthors increases from 9% on papers with three authors to 30% on papers with more than six authors [90], with the most commonly cited reason for accepting undeserved authorship being academic promotion [8].

A far more serious concern are "ghost authors," individuals who made substantive contributions to a publication but who were not acknowledged as authors [100]. Ghost authorship has deep roots in science's historically flawed tradition of credit allocation. Take, for example, Robert Boyle, the most acclaimed chemist in 17th century London. His laboratory was populated with assistants who tended distillations, amalgamations, and rectifications., made observations, and recorded them for Boyle's use [101]. Yet we know absolutely nothing about these researchers or their contributions to the research—not even their names—since Boyle published all their findings and contributions as his own (Fig. 2.6.3).

Unfortunately, this phenomenon has not abated in the centuries since. A recent estimate indicates that more than *half of the papers* in many disciplines have at least one ghost author [99]. The primary victims are often graduate students, whose relegation to ghost author status can hurt their chances of career advancement.

Figure B2.6.3 **Invisible technicians.** Artistic convention helped ensure the lowly technician's invisibility in the seventeenth century by depicting the agents operating scientific instruments as putti, or cherubs, rather than human beings. From Caspar Schott, Mechanica hydraulico-pneumatica [102]. After Shapin [101].

2.6.4 The collaboration penalty for women

Economics, like many other disciplines, remains a stubbornly male-dominated profession. While women are disproportionately more likely to abandon the field at every stage, from high school to post-PhD [103-105], one especially leaky segment of the academic pipeline has puzzled economists for decades: Female economists are twice as likely to be denied tenure as their male colleagues [106, 107]. If we look at all faculty members in economics departments at the top 30 American universities, about 30% of them failed to win tenure at their first institution [107]. Yet, broken down by gender, a giant disparity emerges: 48% of women—nearly half of all female applicants!—were turned down for tenure, compared to just 23% of male applicants.

Why does such a chasm exist? Could it be rooted in different productivity patterns? The answer is no. If we measure the number of publications for both men and women economists before receiving tenure, and account for the prestige of the journals in which these papers were published, we find that the two groups are statistically indistinguishable [107]. Over the years researchers have investigated other plausible explanations, including heterogeneous tenure-granting rates across universities, which subfields of economics women work in, behavioral differences such as competitiveness and confidence [108], and the role of child-bearing. But it turns out, none of these factors can quite explain the gender gap in tenure outcomes [106].[3] As such, a significant portion (over 30%) of the gender promotion gap has remained a puzzling mystery [106, 107].

But recent research has found that the explanation for the gender gap in tenure rates may be quite simple [107]: Women economists face an enormous penalty for collaborating (Fig. 2.6.4). That is, if we sort economists based on their tendency to collaborate—as measured by the fraction of solo-authored papers in an economist's career—female economists who always work alone have exactly the same success rate for receiving tenure as their male counterparts. Indeed, for both male and female economists, each solo-authored paper raises the probability of getting tenure by about 8 or 9 percent. Yet, as soon as their CVs start to include team-authored papers, the two genders part ways.

[3] To be sure, many of these variables do play a role. For example, the family commitment of female faculty is a significant factor, but it mostly explains why women take a year longer on average to be considered for tenure, and has no impact on tenure outcome.

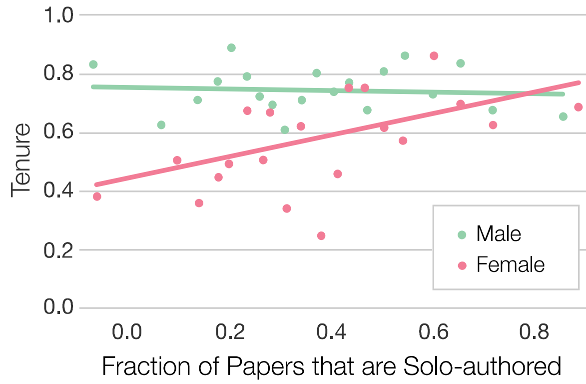


Figure 2.6.4 **Team composition of papers and tenure rate.** Correlation between tenure rate and the fraction of an individual's papers that are solo-authored, split by gender. Both variables are plotted after controlling for the number of years it took to go up for tenure, average journal rank for solo and coauthored publications, total citations, with tenure school, year, and field fixed effects. The line of best fit is shown separately for men and women (N = 552), which shows the slope equals to 0.41 for women and 0.05 for men. After Sarsons [107].

Men get just as much credit for collaborative research as for solo work, meaning that the career prospects of solitary economists and team players are effectively the same for men. However, when women write with female co-authors, the benefit to their career prospects is less than half that accorded to men. Things get especially dismal when women write with men. When a female economist collaborates with one or more male economists, her tenure prospects *don't improve at all*. In other words, when it comes to tenure, women get essentially zero credit if they collaborate with men. The effect is so dramatic that this single variable—the fraction of solo-authored papers—can explain most of gender differences in tenure outcomes.

Could this collaboration-based gender penalty be due to a lack of clear credit allocation protocols in economics? Sociologists, for example, collaborate often, but they explicitly describe who deserves the most credit in a collaboration by listing that person as the first author. Perhaps as a result, tenure rates in sociology are comparable for men and women, even though men tend to produce more solo-authored papers than women. Hence, it appears that by listing authors in order of their contributions, scientists can eliminate the impulse to make inferences and assumptions based on bias. By contrast, most economics papers list authors alphabetically, a process that allows gender-based judgments, however unconscious, to have a devastating power.

*

In this chapter we compared science authorship protocols and their implications for scientific credit. However, the discussion so far only explores how credit *should* have been allocated in principle. But as the tenure gap for female economists illustrates, there are major issues with how scientific credit *is* allocated in practice. This is the focus of the next chapter.

Chapter 2.7

Credit Allocation

Even if you've never heard of the Thomas Theorem, you're likely familiar with the idea. It states, in short: "If men define situations as real, they are real in their consequences." This helps explain, for example, how a mere rumor about a coming food shortage can make people flock to the grocery store to stock up, turning that rumor into a reality. This famous theorem, named after sociologist W. I. Thomas and often credited as the origin of "the self-fulfilling prophecy," first appeared in Thomas' book *The Child in America* [109], a deeply influential text in sociology. Both the Thomas Theorem and *The Child in America* are repeatedly cited as the work of W. I. Thomas alone [110]. But the fact is, the cover of the book lists two authors: W. I. Thomas and Dorothy Swaine Thomas.

In this chapter, we will focus on the question of who ends up getting the credit for a collaborative work. We will see cases where certain researchers benefited, sometimes disproportionately, from a joint work, and other instances where they were unjustifiably overlooked. The truth is that how we allocate credit has a lot to do with bias, and some of these biases are deeply rooted in the way science is practiced. But the good news is, we now have a set of tools at our disposal that can decipher with increasing precision how the scientific community perceives the contribution of each author on any collaborative paper. These tools not only allow us to calculate how credit may be perceived and allocated for a given project—sometimes even before the collaboration begins—but also offer valuable insights about the intricacies and subtleties of how the scientific community allocates credit.

2.7.1 The Matthew Effect, Revisited

W. I. Thomas's unequal recognition for the joint work is an example of the Matthew effect, a process that governs how credit *is* (mis)allocated in science [111]. The Matthew effect states that, when scientists with different levels of eminence are involved in a joint work, the more renowned scientists get disproportionally greater credit, regardless of who did what in the project. Indeed, when Harriet Zuckerman interviewed Nobel laureates for her book [10], one physics laureate put it simply: "The world is peculiar in this matter of how it gives credit. It tends to give the credit to [already] famous people."

The most obvious explanations for this phenomenon are familiarity and visibility. That is, when we read through the list of authors on a paper, the names we don't recognize are effectively meaningless to us, while a name with which we're familiar stands out prominently—and so we immediately associate the paper with the person we already know. More often than not, the familiar name is a more well-known and senior coauthor. In the words of a laureate in Chemistry: "When people see my name on a paper, they are apt to remember *it* and not to remember the other names." [111]. Dorothy Swaine Thomas, whose contribution to *The Child in America* was diminished to the point of vanishing, represents this kind of credit discrimination. When the book was first published in 1928, W. I. Thomas, then 65, was the president of the American Sociological Society, a belated acknowledgement of his longstanding rank as Dean of American Sociologists [111]. Dorothy Swaine Thomas, still in her twenties, was working as W. I. Thomas's assistant and was virtually unknown to the rest of the scientific community.

Box 2.7.1 The Matthew Effect Recap

We encountered the Matthew effect in Chapter 1.3, when we examined individual scientific careers. The Matthew effect operates through multiple channels in science which can be broadly categorized into (1) communication and (2) reward [111]. The Lord Rayleigh example pertains to the former, where scientific status and reputation influences the perception of quality. When his name was inadvertently omitted from the author list, the paper was promptly rejected. Yet, when Rayleigh's true identity was revealed, of course, the work itself remained the same, yet the response to the work changed.

In the reward systems of science, which is the focus of this chapter, the Matthew effect helps ensure that authors of vastly unequal reputation are recognized differently for their contributions. For example, the Matthew effect predicts that when independent discoveries are made by two scientists of different rank, the more famous one will get the credit. The story of Bernard of Chartres is a prime example. Although the 12th-century philosopher coined the saying "Standing on the shoulders of giants" 400 years before Newton penned it in a letter to Robert Hooke, the famous phrase is nevertheless universally attributed to Newton. The Matthew effect also applies when multiple people are involved in the *same* discovery, but a disproportionate share of the credit ends up going to the most eminent collaborator. In this chapter, we treat both cases of the Matthew Effect as stemming from the same credit attribution problem.

The disproportionate credit eminent scientists get when they collaborate with less well-known colleagues poses a dilemma for both junior and senior scientists, as succinctly summarized in Merton's interview with one of the Nobel laureates [24]:

> You have a student; should you put your name on that paper or not? You've contributed to it, but is it better that you shouldn't or should? There are two sides to it. If you don't, there's the possibility that the paper may go quite unrecognized. Nobody reads it. If you do, it might be recognized, but then the student doesn't get enough credit.

Indeed, research confirms that status signals eminence, which can not only increase the visibility of the work but also influence how the community perceives its quality [24, 112, 113]. Plus, through the process of working side by side with the best, a young researcher can also acquire all kinds of tacit knowledge he might not otherwise access, such as insights about a mentor's working habits, how she develops research questions, and how she responds to challenges along the way.

But from a credit perspective, there are serious downsides. Even if you had a chance to coauthor with Einstein, the paper would, first and foremost, always be Einstein's. Even though the junior author may have executed most of the work—which is frequently the case—their efforts will be overshadowed, and they'll end up getting less credit than they deserve.

And another important scenario to ponder: What happens when something goes wrong with the paper, such as a retraction, an issue with plagiarism, or when results are falsified or debunked? Who will be considered at fault? Eminent authors benefit more than they deserve from successful collaborations, precisely because the scientific community assumes that they were the source of the key ideas, while junior coauthor(s) are thought to have merely executed the project. Therefore, it is only reasonable to assume that the eminent author, as the presumed leader of the work, would bear more blame for errors or failures. With greater credit comes greater responsibility—right?

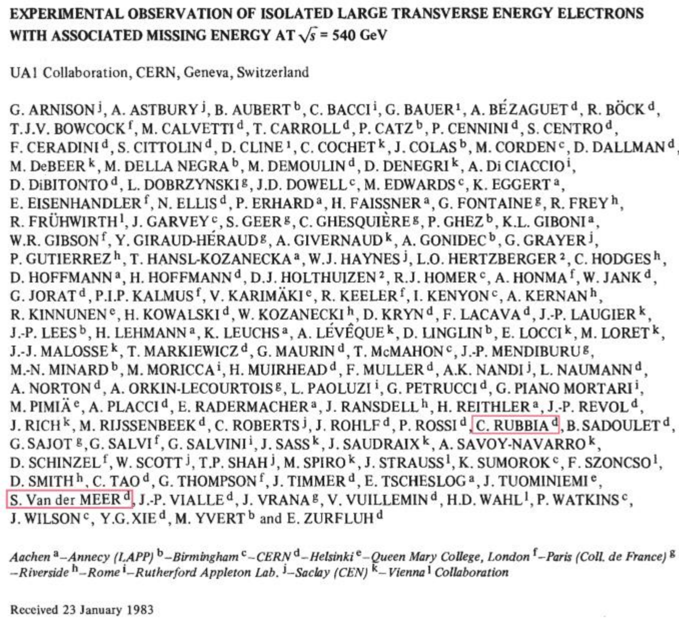
Research shows that exactly the opposite is true. In fact, when senior and junior authors are involved with the *same* retracted papers, senior authors can escape mostly unscathed from the fallout of the retraction while their junior collaborators (typically graduate students or postdoctoral fellows) are often penalized [114], sometimes to a career-ending degree. Therefore, a strong reputation not only assigns disproportionate credit to an eminent researcher; it also protects them in the event of a catastrophe. The underlying logic is quite simple: If Einstein coauthors a paper that is retracted, how could such a retraction possibly be Einstein's fault?

Box 2.7.2 The Reverse Matthew Effect, Recap

As you may recall, when researchers compared retracted papers to closely-matched control papers [115] and non-retracted control authors [116], they found that retractions led authors to experience citation losses in their prior body of work [115-117], and eminent scientists were more harshly penalized than their less-distinguished peers in the wake of a retraction [116] (See also Box 1.3.3 *From Boom to Bust* in Ch. 1.3). Confusingly, these results appear to be at odds with what is discussed here. The key distinction between the two findings is whether we compare the citation penalties *within* teams or *between* them. When authors are on the same team, which is what this chapter concerns, the community assumes the fault lies with junior authors. Yet, if we compare two different papers, one by eminent authors and the other by relatively unknown authors, the results in Ch. 1.3 show that the former are more harshly penalized than the latter.

These results reveal a harsh reality about science: Credit is collectively determined by the scientific community, not by individual coauthors. Indeed, individual team-members are often left helpless when their true contribution differs from what is perceived by the community. Still, there's a silver lining. Scientific credit follows precise rules that are not easily swayed by individual wills—which means, if we can decipher what these rules are, we can then follow them to calculate and even predict who will be seen as responsible for a discovery. By doing so, we can empower scientists to protect their share of the credit on team projects, and to ensure fair allocation of credit to coauthors.

2.7.2 Collective credit allocation


EXPERIMENTAL OBSERVATION OF ISOLATED LARGE TRANSVERSE ENERGY ELECTRONS WITH ASSOCIATED MISSING ENERGY AT $\sqrt{s}$ = 540 GeV

UA1 Collaboration, CERN, Geneva, Switzerland

G. ARNISON[j], A. ASTBURY[j], B. AUBERT[b], C. BACCI[i], G. BAUER[1], A. BÉZAGUET[d], R. BÖCK[d], T.J.V. BOWCOCK[f], M. CALVETTI[d], T. CARROLL[d], P. CATZ[b], P. CENNINI[d], S. CENTRO[d], F. CERADINI[d], S. CITTOLIN[d], D. CLINE[1], C. COCHET[k], J. COLAS[b], M. CORDEN[c], D. DALLMAN[d], M. DeBEER[k], M. DELLA NEGRA[b], M. DEMOULIN[d], D. DENEGRI[k], A. Di CIACCIO[i], D. DiBITONTO[d], L. DOBRZYNSKI[g], J.D. DOWELL[c], M. EDWARDS[c], K. EGGERT[a], E. EISENHANDLER[f], N. ELLIS[d], P. ERHARD[a], H. FAISSNER[a], G. FONTAINE[g], R. FREY[h], R. FRÜHWIRTH[l], J. GARVEY[c], S. GEER[g], C. GHESQUIÈRE[g], P. GHEZ[b], K.L. GIBONI[a], W.R. GIBSON[f], Y. GIRAUD-HÉRAUD[g], A. GIVERNAUD[k], A. GONIDEC[b], G. GRAYER[j], P. GUTIERREZ[h], T. HANSL-KOZANECKA[a], W.J. HAYNES[j], L.O. HERTZBERGER[2], C. HODGES[h], D. HOFFMANN[a], H. HOFFMANN[d], D.J. HOLTHUIZEN[2], R.J. HOMER[c], A. HONMA[f], W. JANK[d], G. JORAT[d], P.I.P. KALMUS[f], V. KARIMÄKI[e], R. KEELER[f], I. KENYON[c], A. KERNAN[h], R. KINNUNEN[e], H. KOWALSKI[d], W. KOZANECKI[h], D. KRYN[d], F. LACAVA[d], J.-P. LAUGIER[k], J.-P. LEES[b], H. LEHMANN[a], K. LEUCHS[a], A. LÉVÊQUE[k], D. LINGLIN[b], E. LOCCI[k], M. LORET[k], J.-J. MALOSSE[k], T. MARKIEWICZ[d], G. MAURIN[d], T. McMAHON[c], J.-P. MENDIBURU[g], M.-N. MINARD[b], M. MORICCA[i], H. MUIRHEAD[d], F. MULLER[d], A.K. NANDI[j], L. NAUMANN[d], A. NORTON[d], A. ORKIN-LECOURTOIS[g], L. PAOLUZI[i], G. PETRUCCI[d], G. PIANO MORTARI[i], M. PIMIÄ[e], A. PLACCI[d], E. RADERMACHER[a], J. RANSDELL[h], H. REITHLER[a], J.-P. REVOL[d], J. RICH[k], M. RIJSSENBEEK[d], C. ROBERTS[j], J. ROHLF[d], P. ROSSI[d], C. RUBBIA[d], B. SADOULET[d], G. SAJOT[g], G. SALVI[f], G. SALVINI[i], J. SASS[k], J. SAUDRAIX[k], A. SAVOY-NAVARRO[k], D. SCHINZEL[f], W. SCOTT[j], T.P. SHAH[j], M. SPIRO[k], J. STRAUSS[l], K. SUMOROK[c], F. SZONCSO[l], D. SMITH[h], C. TAO[d], G. THOMPSON[f], J. TIMMER[d], E. TSCHESLOG[a], J. TUOMINIEMI[e], S. Van der MEER[d], J.-P. VIALLE[d], J. VRANA[g], V. VUILLEMIN[d], H.D. WAHL[l], P. WATKINS[c], J. WILSON[c], Y.G. XIE[d], M. YVERT[b] and E. ZURFLUH[d]

Aachen [a]–Annecy (LAPP) [b]–Birmingham [c]–CERN [d]–Helsinki [e]–Queen Mary College, London [f]–Paris (Coll. de France) [g]–Riverside [h]–Rome [i]–Rutherford Appleton Lab. [j]–Saclay (CEN) [k]–Vienna [l] Collaboration

Received 23 January 1983

Figure 2.7.1 **The Nobel Prize in Physics 1984.** Screenshot of the paper reporting the discovery of the particles *W* and *Z* [118], based on which the 1984 Nobel Prize in Physics was awarded jointly to two of the paper's coauthors, Carlo Rubbia and Simon van der Meer, "for their decisive contributions to the large project, which led to the discovery of the field particles *W* and *Z*, communicators of weak interaction."

The paper shown in Fig. 2.7.1, which reported the discovery of the *W* and *Z* bosons [118], was awarded the Nobel Prize in Physics the year after its publication, an exceptionally quick turn-around between discovery and recognition. But who of the 135 authors alphabetically listed on the paper deserved the Nobel? For high-energy physicists, the answer is a no-brainer: The credit undoubtedly goes to Carlo Rubbia and Simon van der Meer—and only to the two of them—given their "decisive contributions to the large project," to use the words of the Nobel committee. Yet, for anyone else, picking these two out of a long list of authors seems like nothing short of magic.

Clearly, the scientific community uses an informal credit allocation system that requires significant domain expertise. But for those outside of the discipline, is there a way to know who was central to a discovery? In the previous chapter (Ch. 2.6), we learned some useful rules of thumb to infer credit. For example, when authors are ordered based on their contributions, we know that we should often pay attention to the first and last authors. But, if you ask us to choose between the first and last author—let alone to pick two out of over a hundred names listed alphabetically as in Fig. 2.7.1—we are lost. Thankfully, we have developed an algorithm that performs this magic, capturing the collective process through which scientific credit is allocated [119], and offering a tool for calculating the share of credit among coauthors for any publication.

To understand how the algorithm works, imagine two authors, Mary and Peter, and their joint publication p_0 (Fig. 2.7.2a). Who gets the credit for this paper? One way to surmise the answer is by examining who has more proven expertise on the subject matter. For instance, consider one extreme case where Mary has published several other papers on the topic, whereas p_0 is Peter's only publication on this topic. This fact can be detected through citation patterns: if we look at papers that tend to be cited together with p_0, several of them will be authored by Mary, yet none by Peter. This means Mary has a well-established reputation in the community, whereas Peter is effectively an outsider. As a result, the community is more likely to view the paper $p_{0,}$ as a part of Mary's body of work, rather than Peter's (Fig. 2.7.2a).

Ei-ichi Negishi, who won the 2010 Nobel prize in Chemistry for his joint 1976 paper with Shigeru Baba (Fig. 2.7.2b) exemplifies this scenario. Although Baba co-authored the landmark paper, it was his only high-profile publication on the topic. In contrast, Negishi published several other highly cited papers in subsequent years. When the Nobel had to decide, they awarded the prize to Negishi alone.

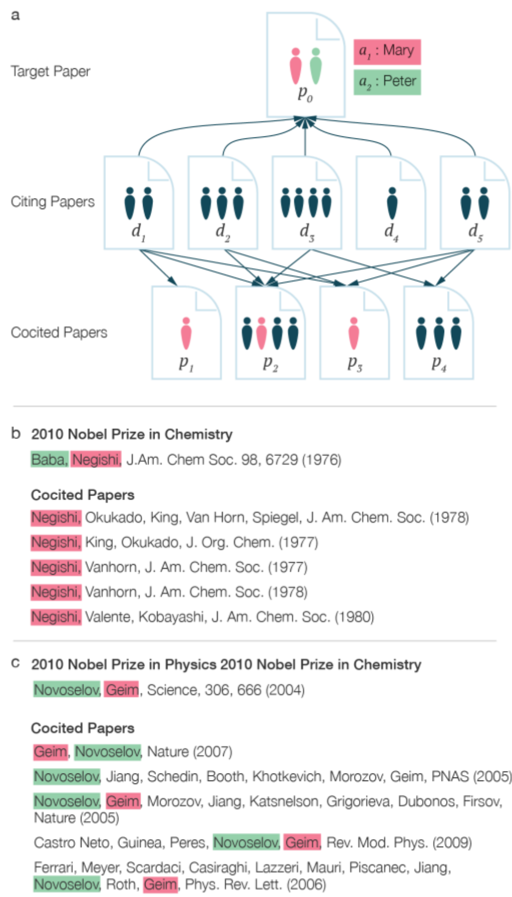


Figure 2.7.2 **Collective credit allocation in science.** (a) illustrates one extreme case of how credit allocation works in science: when Peter contributes to only one paper in a body of work, the community assigns most of the credit to Mary, who publishes multiple papers on the topic. (b) and (c) show two case studies of credit allocations. Negishi exemplifies the example shown in A, as he published several other papers in this area that are co-cited by the community with the Nobel-winning paper on the top. Yet, the prize-winning paper was the only one published by his coauthor Baba. By contrast, in Case B, Novoselov and Geim were jointly involved in almost all highly co-cited papers on the subject and were jointly awarded the Nobel prize with an equal share. After Shen and Barabasi [119].

Consider the other extreme case, shown in Fig. 2.7.2c. In this case, *all* highly cited papers pertaining to the topic of p_0 are joint publications between the same two scientists, Novoselov and Geim. If the two scientists always share authorship, an observer without any outside information must give both authors equal credit for p_0. Their joint Nobel prize for the discovery of graphene is an excellent example of this scenario: Novoselov and Geim not only co-authored the first paper on graphene, but were also jointly involved in almost all high-impact publications on the topic afterwards, earning them an equal share of credit for the original discovery.

Clearly, however, most cases are more complicated, lying somewhere in between the two extremes. The two authors may publish some papers together, and some papers with other coauthors on similar topics. Hence their credit share for a particular work may change with time. So how can we quantify the proportion of "the body of work" allocated to each coauthor? We can inspect the co-citation patterns between the paper in question and all other papers published by the same authors. Figure 2.7.3 illustrates a collective credit allocation algorithm that allows us to do just that [119]. To get a sense of how this works, we discuss credit allocation for a paper with two arbitrary coauthors in Fig. 2.7.3.

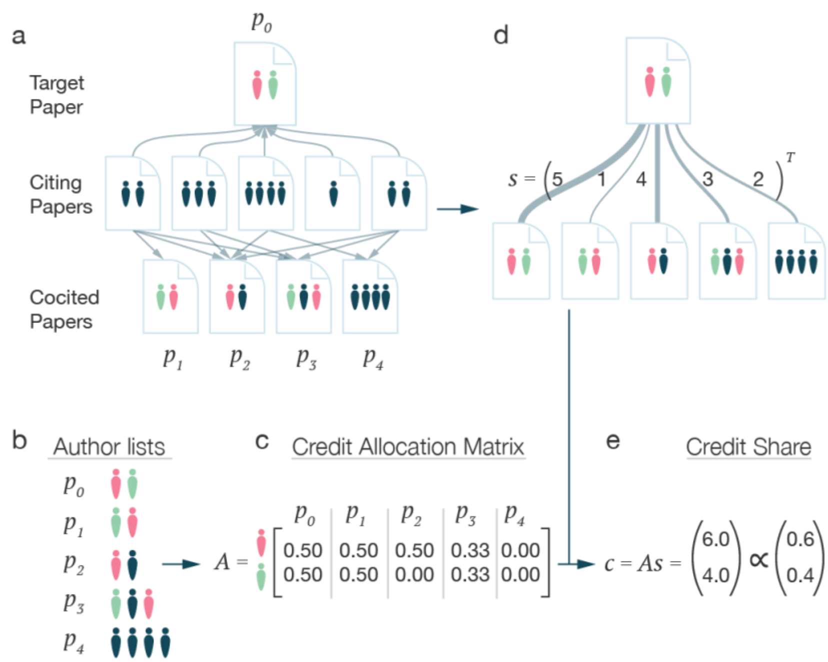


Figure 2.7.3 **An illustration of a collective credit allocation algorithm [119]**. (a) The target paper p_0 has two authors, colored in red and green, respectively. To determine the credit share going to each of the two authors for their joint paper p_0, we first identify all papers that cite p_0: $\{d_0, d_1, \cdots, d_5\}$. We then trace their references to identify all other papers co-cited with p_0, $P \equiv \{p_0, p_1, \cdots, p_4\}$. The set of papers P thus represent the total body of work specifically related to p_0, as every time p_0 is referenced in the literature, it appeared together with papers in P. Next, we seek to discover the involvement of the two authors within this body of work P. As shown in (b), we can first go through all papers in P and calculate their involvement in $p_0, p_1, \cdots, p_4$. In the example shown in A, both authors are assigned equal (half) credit for p_0 and p_1, as they are the only two authors involved in these papers. But for p_2, only the red author is involved within a two-author team, hence he is assigned 0.5 credit, while the green author receives 0 for this paper. Repeating this process for all papers in P, we can obtain an authorship involvement matrix $\mathbf{A}$, where each element A_{ij} denotes the amount of credit that each author gets from each paper p_j published on this topic. (c) The credit allocation matrix A obtained from the author lists of the co-cited papers in (B). The matrix A provides the author's share for each co-cited paper. For example, because p_2 has the red author as one of its two authors but it lacks the green author, it provides 0.5 for the red author a_1 and 0.0 for the green author. Yet, not all papers in P are the same: some papers are more relevant than others to p_0. This can

be resolved by calculating the co-citation strength s_j between p_0 and any given paper in P, p_j, which measures the number of times p_0 and p_j are cited together. This process is illustrated in (d), showing the p_0-centric co-citation network constructed from (A), where the weights of links denote the co-citation strength s between the co-cited papers and the target paper p_0. For example, in A, p_1 has only been cited once with p_0 (through d_1), whereas p_2 and p_0 have been cited in tandem by four different papers (d_1, d_2, d_3, d_5). Therefore, insofar as p_0 is concerned, p_2 should have a higher co-citation strength (i.e., $s_1 = 1$ vs. $s_2 = 4$) than p_1, meaning it is likely to be more closely related. (e) With the matrix A and co-citation strength s, the credit share of the two authors of p_0 is computed by the multiplication of the two matrices with a proper normalization. The ultimate credit allocated to each author by the algorithm is simply their involvement in the body of work, weighted by the relevance of that work. Mathematically, this corresponds to the multiplication of author involvement matrix and co-citation strength matrix, **c = As.** After Shen and Barabasi [119].

In the algorithm outlined in Fig 2.7.3, each additional paper conveys implicit information about the author's perceived contribution, capturing, in a discipline-independent fashion, how the scientific community assigns credit to each paper. This algorithm is not only a theoretical tool: when applied to all multi-author Nobel prize-winning publications, the method correctly identified the laureates as the authors deserving the most credit 81% of the time (or, in 51 out of 63 papers). Regardless of whether the winner was in high physics, where authors are listed alphabetically, or in biology, where a team's leader is usually the first or last author, the algorithm consistently predicted the winners. And in the 19% of cases where the algorithm picked the wrong person, it often revealed interesting tensions and potential misallocations worthy of further consideration (see Box 2.7.3).

Box 2.7.3 When the credit allocation algorithm fails:

While it's fascinating to see the algorithm automatically identify prizewinners from long lists of names, it's equally interesting to witness the method fail [119]. This would imply that there are individuals who, in the eyes of the community, likely deserve major credit for a discovery, but were nevertheless overlooked by the Nobel committee. One example is the 2013 Nobel prize in Physics, awarded for the discovery of the "God Particle," the Higgs Boson. Six physicists are credited for the 1964 theory that predicted the Higgs boson, but the prize could only be shared by a maximum of three individuals. F. Englert and R. Brout published the theory first [120], but failed to flesh out the Higgs boson, whose existence was predicted in a subsequent paper by P. W. Higgs [121]. G. S. Guralnik, C. R. Hagen, and T. W. B. Kibble independently proposed the same theory and published a month after Englert and Brout [122], explaining how the building blocks of the universe get their mass. In 2010, the six physicists were given equal recognition by the American Physical Society (APS), sharing the Sakurai prize for theoretical particle physics. Yet, the Nobel committee awarded the prize only to Higgs and Englert in 2013. The credit allocation algorithm predicts that Higgs would get the most credit, followed by Kibble. Englert, however, is the third, with only a slightly higher credit share than his coauthor Brout, who died before the Noble was awarded. Guralnik and Hagen equally share the remaining credit. This means that, according to the algorithm, the 2013 Nobel Physics prize should have gone to Higgs, Kibble, and Englert in that order. By passing over Kibble, the committee deviated from the community's perception of where the credit lies.

A similar mismatch between the real-world laureates and the algorithm's prediction brought Douglas Prasher to our attention. In 2008, when the Nobel prize was awarded, his credit share for the discovery of GFP was 0.199, thanks to the many highly cited key papers he coauthored on the topic. While this share was smaller than two of the laureates' Tsien's, and Shimomura (0.47 and 0.25, respectively), it exceeded the share belonging to Martin Chalfie (0.09), who also received the award.

The credit allocation algorithm tells us that when we allocate credit to team members, we don't need to know who actually did the work. This underlines an important message: Scientific credit is not just about contribution—it's also about perception. As such, this chapter doesn't just offer us a quantitative tool that can help us calculate credit share for joint publications. It also offers several insights regarding the nature of collaboration.

Lesson 1: In science, it is not enough to publish a breakthrough work and simply wait to be recognized for it. To claim your well-deserved credit in the eyes of others, you must continue publishing work of importance independent of your previous coauthors. You need to be seen by the community as the consistent intellectual leader behind your earlier breakthrough work, and your contribution to the original paper matters little in shaping this perception. Rather, as the algorithm illustrates, what you publish *after* the breakthrough in question is what ultimately determines your share of credit.

Lesson 2: If you venture into an established area—for instance, beginning your career working with experts in your field—your credit share may be pre-determined at the outset. Indeed, if your coauthors have done significant work on a topic you are just beginning to explore, their previous work will likely be co-cited with the current paper. In this case, even if you subsequently manage to publish many relevant works afterwards—and do so independently of your original coauthors—it may take a long time for you to overcome the pre-existing credit deficit, if it ever happens at all. After all, if papers that cite your new work also cite past canonical works by your coauthors in the area, it will dilute your additional effort.

There are many reasons to pursue a particular research project. We may join a team because we like working with the team members, because we believe in its mission, or because there is a big problem to be solved. In other words, we often join a team without caring about who gets the credit for the work. But if we *do* seek credit, then the algorithm can help us determine ahead of time whether we can ever hope to gain a noticeable credit for the team's work (See also Box 2.7.4).

Box 2.7.4 The credit allocation algorithm may raise incentive issues.

By quantitatively exposing the informal credit system, algorithms, like the one we discussed in this chapter, allow anyone to calculate their perceived credit share even before a team has officially formed, which may have unintended consequences [12, 19]. For example, individuals may be encouraged to select collaborators partly based on ex-post credit considerations rather than the effectiveness of the team itself. Will the availability of such methods make collaborations more strategic? And if so, what can we do to counter-balance personal interests against the collective advance of science? We do not have answers to these questions. But, as our approach to understanding the mechanisms within science becomes increasingly more scientific, it would allow us to anticipate and detect new side effects earlier, and with a better diagnosis.

*

Alas, Dorothy Swaine Thomas faced two challenges at the time—she was not only a junior researcher collaborating with an established partner, but also a woman in an era when the scientific community regularly downplayed the contributions of women. However, her story does not end in obscurity: She eventually went on to have a distinguished scientific career, achieving a prominent reputation of her own. Like W. I. Thomas, she too was elected to the presidency of the American Sociological Society in 1952. But none of these achievements prevented even the most meticulous scholars from attributing the 1928 book solely to her famous coauthor, a practice that continues even today. What's more, as this chapter makes clear, had it not been for her later stellar career, we may not be grumbling about the omission of her name in the first place—she might have been lost to history entirely.

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