

**Supplementary Information for Scientific elite revisited: Patterns of
productivity, collaboration, authorship and impact**

Jichao Li^{1,2,3,4}, Yian Yin^{2,3,5}, Santo Fortunato^{6,7} and Dashun Wang^{2,3,4,5*}

¹ *College of Systems Engineering, National University of Defense Technology, Changsha, China*

² *Center for Science of Science and Innovation, Northwestern University, Evanston, IL, USA.*

³ *Northwestern Institute on Complex Systems, Northwestern University, Evanston, IL, USA.*

⁴ *Kellogg School of Management, Northwestern University, Evanston, IL, USA*

⁵ *McCormick School of Engineering, Northwestern University, Evanston, IL, USA*

⁶ *School of Informatics, Computing, and Engineering, Indiana University, Bloomington, IN, USA*

⁷ *Indiana University Network Science Institute (IUNI), Indiana University, Bloomington, IN, USA*

Contents

S1	Data Description	3
S1.1	Dataset of career histories for Nobel laureates	3
S1.2	Comparison dataset	3
S1.3	Data preprocessing	3
S2	Literature Review of Nobel Prize Studies.....	4
S3	Supporting Information for Figure 1.....	5
S3.1	Hit paper rate	5
S3.2	Robustness check of Fig. 1d	6
S3.3	Robustness check of early career length.....	6
S4	Supporting Information for Figure 2.....	7
S4.1	Normalized joint probability between the three most cited papers	7
S4.2	Normalized joint probability between prize-winning papers and hit works	7
S4.3	Hot-streak model	7
S4.4	Fitting the hot-streak model	8
S4.5	Parameters of the generative hot-streak model	8
S4.6	Number and duration of hot streaks	9
S5	Supporting Information for Figure 3.....	9
S5.1	Selecting adjacent papers	9
S5.2	Authorship analysis controlling for temporal factors.....	9
S5.3	Authorship analysis for hit works	10
S6	Supporting Information for Figure 4.....	10
S6.1	Hit paper rate changes after the Prize.....	10
S6.2	Robustness check of disciplines	11
S6.3	Robustness check of publication time.....	11
S6.4	Nobel dip after controlling for the burst.....	11
S6.5	Topic changing after winning the Nobel Prize.....	12
S6.6	Topic identification based on Infomap algorithm	12
S6.7	The popularity of research topics before and after the Prize	13
S6.8	Changes in collaborators before and after the Prize	13
S6.9	Funding opportunities before and after the Prize	14
S7	Supplementary Figures	15
	Reference.....	27

S1 Data Description

S1.1 Dataset of career histories for Nobel laureates

In this project, we manually gather 874 prize-winning papers for 545 Nobel laureates. The prize-winning papers are then matched in the Microsoft Academic Graph (MAG) database. We also construct a unique dataset of publication lists of 93,394 laureate papers for almost all (545 out of 590, or 92.4%) Nobel laureates by manually combining information collected from Nobel Prize official websites, the laureates' university websites, and Wikipedia, and matching laureates with their publications from the MAG database. The dataset obtained through this process is validated with external sources from manually collected CVs, selected Google Scholar (GS) profiles, additional affiliation information, and manual verification of a random selection of 60 Nobel laureates (20 for each Nobel laureate). The collected publication records can be downloaded at <https://doi.org/10.7910/DVN/6NJ5RN>. The manual curation and algorithmic disambiguation procedures for collecting the publication records of the Nobel laureates are detailed in our paper¹.

S1.2 Comparison dataset

We also leverage a dataset of over 20,040 carefully disambiguated typical authors from GS² as our comparison group. To show the cross-domain difference between laureates and typical authors, typical authors are classified in each of the three Nobel fields if they have published at least one paper in a related field. The Nobel field categories for physics, chemistry, and medicine are referred to Jones's paper³. Most typical authors in the GS dataset have produced work in recent decades. To eliminate this temporary effect, we only consider Nobel laureates and typical scientists whose first paper was published after 1960 and whose careers were at least 10 years in length. For each Nobel laureate who published her first paper after 1960, we randomly match 20 typical authors in the same research domain with the same first-paper publishing year, which eventually resulted in 3540 authors (1260 in physics, 1140 in chemistry, and 1140 in medicine) randomly matched to 177 Nobel laureates (63 in physics, 57 in chemistry, and 57 in medicine).

S1.3 Data preprocessing

To ensure the feasibility and reliability of the results, the raw data is processed in the following ways for further analysis: 1) We only focus on the laureates' original papers, meaning that all review and note papers are removed; 2) Nobel lecture papers are also removed; 3) When performing citation analysis, we only focus on papers published before 2005 to ensure that all analyzed papers garner 10 years of citations.

S2 Literature Review of Nobel Prize Studies

The Nobel Prize, commonly perceived as the highest honor that a natural scientist could ever have, has been frequently used as a proxy for identifying top researchers of supreme achievement. A large body of literature in disciplines ranging from sociology, economics, psychology, and physics has focused on these scientific ultra-elites, which can be summarized into two main streams: quantitative and qualitative study. On the one hand, quantitative study is based on the laureate's publication and citation records, primarily their milestone events, i.e. their prize-winning research. Topics related to these milestones include scientific creativity, credit allocation, breakthrough recognition, collaboration patterns, and changing citation dynamics. However, most of the literature is focused on either one specific domain or a small percent of the laureates, resulting from an incomprehensive dataset. On the other hand, qualitative research aims to understand laureates' entire careers, often by examining Nobel archives or interviewing prizewinners. The most representative work in this area is from Zuckerman, who interviewed 45 American Nobel laureates, systematically examining each career in detail. Table S1 reviews selected studies related to the Nobel Prize.

Table S1: Literature review of Nobel Prize studies

Year	Paper	Category	Topic	Data
1957	Manniche et al. (1957) ⁴	quantitative & qualitative	Age and creativity	164 prizewinners in the period 1901-1950
1967	Zuckerman (1967) ⁵	quantitative	Nobel prestige	Affiliation information of 76 prize-winners
1967	Zuckerman (1967) ⁶	quantitative & qualitative	Productivity, collaboration and authorship	Interview information from 41 prize-winners
1977	Zuckerman (1977) ⁷	quantitative & qualitative	Productivity, collaboration and authorship	Interview information from 41 prize-winners
1978	Ashton et al. (1978) ⁸	quantitative	Citation analysis	Citation record of Nobel prizewinner, W. N. Lipscomb
1984	Crawford (1984) ⁹	qualitative	Documented study	Nobel Archives between 1901-1915
1986	Garfield (1986) ¹⁰	quantitative	Citation analysis	Citation records of 125 prizewinners from 1965 to 1984
1988	Diamond (1988) ¹¹	quantitative	Citation analysis	Citation counts of 24 prizewinners in economics between 1969 and 1986
1991	MacLauchlan (1991) ¹²	quantitative & qualitative	Nobel nominations study	Nobel Archives between 1901 and 1937
1992	Garfield (1992) ¹³	quantitative	Citation analysis	Citation records of 37 prizewinners between 1961 and 1976
1999	Van Dalen (1999) ¹⁴	quantitative	Age and creativity	Productivity record of Nobel Prize laureates in economics, 1969-1997
2000	Rodgers (2000) ¹⁵	qualitative	How the winners are selected	/
2000	Feldman (2000) ¹⁶	qualitative	The history of Nobel Prize	/
2001	Friedman (2001) ¹⁷	qualitative	Politics of excellence	Nobel Archives up to 1950
2001	Crawford (2001) ¹⁸	qualitative	How the winners are selected	Nobel population 1901-1950
2002	Crawford (2002) ¹⁹	qualitative	Social history of science	Nobel Archives between 1901 and 1939
2003	James (2003) ²⁰	qualitative	Academic success	/
2003	Friedman (2003) ²¹	qualitative	Prize recognition	/
2005	Hirsch (2005) ²²	quantitative	Citation analysis	Physicists who earned Nobel Prizes between 1985 and 2005
2006	Wray (2006) ²³	qualitative	Collaboration and authorship	/

Year	Paper	Category	Topic	Data
2008	Rablen (2008) ²⁴	quantitative	Age analysis	Nobel Prize winners and nominees in physics and chemistry between 1901 and 1950
2010	Gingras (2010) ²⁵	quantitative	Specialty increasing	Meta-data of nominees and winners of the chemistry and physics prizes (1901–2007)
2011	Rodríguez-Navarro (2011) ²⁶	quantitative	Nobel prestige	Number of Nobel Prize achievements from 1989–2008
2011	Jones et al. (2011) ³	quantitative	Age and creativity	A dataset of 525 Nobel Prize winners
2011	Mazloumian et al. (2011) ²⁷	quantitative	Citation analysis around landmark paper	Citation records for 124 Nobel Prize laureates
2011	John et al. (2011) ²⁸	quantitative	Recognition lag	Meta-data of Nobel laureates, 1901–2009
2013	Heinze et al. (2013) ²⁹	quantitative	Citation analysis	Citation records of prizewinners Gerd Binnig, Heinrich Rohrer, Harold Kroto, Richard Smalley, and Robert Curl
2013	Chan et al. (2013) ³⁰	quantitative	Recognition lag	466 recipients of Nobel Prizes in physics, Chemistry, and Physiology or medicine awarded from 1901 to 2000
2014	Azoulay et al. (2014) ³¹	quantitative	Citation analysis	16 Howard Hughes Medical Investigator prizewinners
2014	Liu et al. (2014) ³²	quantitative	Citation analysis	Citation data of six Nobel Prize-winning articles
2014	Santo et al. (2014) ³³	quantitative	Recognition lag	Meta-data of Nobel laureates before 2014
2015	Caroline et al. (2015) ³⁴	quantitative	Collaboration and authorship	Meta-data of 68 Nobel Laureates in Physiology or medicine between 1969 and 2011
2016	Hanson et al. (2016) ³⁵	qualitative	How the winners are selected	/
2017	Sondhi et al. (2017) ³⁶	qualitative	Prize-granting entities	/
2017	Seeman (2017) ³⁷	qualitative	Prize recognition	Nobel Prizes for organic chemistry research since 1965
2018	Hanson et al. (2018) ³⁸	quantitative	Winning formula	Hundreds of nominations for the Nobel Prize in Physiology or medicine for the period 1901–66
2018	Ferry (2018) ³⁹	qualitative	Road to Prize	/
2019	Weinberg et al. (2019) ⁴⁰	quantitative	Age and creativity	Citation records of Nobel laureate economists born in or before 1926

S3 Supporting Information for Figure 1

S3.1 Hit paper rate

In Fig. 1b of the main text, we compare the “hit” paper rate—defined as the probability of publishing papers in the top 1% of citations in the same year and field—for Nobel laureates and typical authors. Our collected Nobel laureate dataset is based on information provided by the MAG, which assigns the field of subject for each paper. It is worth noting that the field of subject is a hierarchical structure with six levels. The first level contains 19 main fields, such as “physics,” “chemistry,” “medicine,” and “biology.” The second level contains 295 subfields, such as “astrophysics,” “biophysics,” and “geophysics.” In this paper, we choose the second level fields in calculating the hit paper rate for Nobel laureates. The GS typical scientist dataset is based on information from the WOS, and it is almost impossible to precisely match the career histories of 3540 GS scientists from the WOS to the MAG. Thus, the hit rate analysis of the GS scientists is based on the WOS database itself. Papers in the WOS are also assigned to one of 234 specific field categories, such as “astronomy & astrophysics,” “biophysics,” and “geochemistry & geophysics.” The hit paper rate for typical scientists is calculated using these 234 specific fields from the WOS.

We then compare the hit paper rate for Nobel laureates with typical authors for both single-authored and joint papers after removing prize-winning papers. As we can

see from Fig. S1, the top 1% hit paper rate of single-authored papers for laureates shows a 6.7-fold increase over their peers. In the case of team-authored papers, laureates experience a 4.7-fold increase.

We also compare the top 5% hit paper rate for Nobel laureates and typical authors after removing prize-winning papers. We find that Nobel laureates experience, on average, a 3.1-fold increase over their peers. That number is 3.9-fold and 2.9-fold for single-authored paper and team-authored papers respectively (Fig. S2).

S3.2 Robustness check of Fig. 1d

In the main text (Fig. 1d), we measure the proportion of prize-winning papers written early in a career among all single-authored papers and team-authored papers, respectively. We find that early-stage single-authored papers have a higher chance of being prize-winning than early-stage team-authored papers, especially in physics and chemistry. Does this phenomenon change over time? Here we measure the fraction of early-stage prize-winning papers as a function of year of publication (Fig. S3). Though the average fraction of early-stage prize-winning papers decreases over time, the proportion of prize-winning papers in the single-authored category is always higher than that in the team-authored category (p -value $<10^{-3}$). In conclusion, our results are robust over time.

We also measure the proportion of single-authored papers among all early-stage papers and prize-winning papers respectively. The fraction of single-authored papers within early-stage, prize-winning papers is much higher than that within early-stage, non-prize-winning papers (Fig. S4). Almost 40% of early-stage, prize-winning papers are single-authored, but that fraction is less than 25% of the early-stage, non-prize-winning papers category (p -value $<10^{-11}$). This conclusion is consistent across the three disciplines (physics: p -value $<10^{-5}$; Chemistry: p -value $<10^{-3}$; medicine: p -value=0.014), and the results are robust concerning different periods (Fig. S5). Although the fraction of single-authored papers is decreasing over time, the proportion of early-stage, prize-winning papers that are single-authored is still higher than that of early-stage papers more generally (p -value $<10^{-3}$).

More interestingly, the advantage that comes with single-authoring a paper does not remain consistent over the course of a career. Rather, early-stage scientists experience the strongest benefit from single-authoring. Such benefit decays systematically as scientist ages, reaching a balance point after roughly 30 years when prize-winning papers have relatively the same chance of being single-authored or written jointly (Fig. S6). We drew the same conclusion with respect to a person's overall odds of writing a prize-winning paper. (Fig. S7).

S3.3 Robustness check of early career length

When we refer to “early career” or “early stage” in the main text, we mean the initial five years after a given scientist publishes her first paper. Do our findings still hold if we adjust the early career length? To answer this question, we repeated the same

analysis shown in Fig. 1 for the first four and six years of the careers of both laureates and typical scientists, finding the same productivity and impact patterns (Figs. S8-9).

S4 Supporting Information for Figure 2

S4.1 Normalized joint probability between the three most cited papers

We quantify the relative timing between the three most cited papers (N^* , N^{**} and N^{***}) within each career by calculating the joint probability $P(N^*, N^{**})$, $P(N^*, N^{***})$ and $P(N^{**}, N^{***})$ compared with a null model in which the three papers each follow their independent temporal patterns. We uncovered clear diagonal patterns across all three domains (Figs. S10a-c), showing that high-impact papers by the laureates are more likely to cluster together than expected by chance. The diagonal pattern disappeared when we shuffle the order of the works while preserving the random impact rule (Figs. S10d-f).

S4.2 Normalized joint probability between prize-winning papers and hit works

The documented diagonal pattern prompts us to ask if a similar pattern exists between prize-winning papers and highest-impact works. Here we measure the normalized joint probability of a prize-winning paper (for Nobel laureates with multiple prize-winning papers, we take the average; the same below) and the top three highest impact works within a career before the Prize. Figures S11a-c show clear colocation diagonal patterns between prize-winning papers and the laureates' hit works. If we shuffle the order of each work in a career before the Prize while keeping each paper's impact, the pattern disappears (Figs. S11d-f).

S4.3 Hot-streak model

We find that the career histories of laureates exhibit patterns that are broadly consistent with the hot-streak model². Here, we introduce the hot-streak model. The impact of work, i , produced by an individual can be quantified by $\Gamma_i = \log(\widehat{C}_{10} + 1)$, where \widehat{C}_{10} measures the rescaled number of citations within 10 years of publication (S3.1). Recently, a ubiquitous hot-streak phenomenon has been confirmed as a fundamental law governing a scientist's dynamics of academic performance². It is shown that the vast majority of scientists have at least one hot-streak period, when an individual's performance is substantially higher than her typical performance, which can be curved with a step function:

$$\Gamma(t) = \begin{cases} \Gamma_H & t_{\uparrow} \leq t \leq t_{\downarrow} \\ \Gamma_0 & \text{otherwise} \end{cases}$$

The function features an individual's performance deviations from a baseline performance Γ_0 at a certain point in a career t_\uparrow , elevating to a higher value Γ_H . After sustaining $t_H = t_\downarrow - t_\uparrow$, the individual's performance then falls back to a level similar to Γ_0 .

S4.4 Fitting the hot-streak model

The procedure to fit an individual career performance using the hot-streak model is well-documented in existing study². To evaluate the goodness-of-fit of the hot-streak model, we measure the difference between fitted and real paper impact by calculating the coefficient of determination R^2 . The coefficient of determination R^2 is defined with the following formula:

$$R^2 = \text{MSS}/\text{TSS} = (\text{TSS} - \text{RSS})/\text{TSS},$$

where MSS is the model sum of squares (also known as ESS, or explained sum of squares), which is the sum of the squares of the prediction minus the mean for that variable; TSS is the total sum of squares associated with the outcome variable, which is the sum of the squares of the measurements minus their mean; and RSS is the residual sum of squares, which is the sum of the squares of the measurements minus the prediction from the model.

We fit the career performance of each laureate using the hot-streak model and measure the R^2 between the step-function-simulated career and the real career for all Nobel winners in our dataset. We find the R^2 peaks around 0.75, suggesting that the hot-streak model can capture the career performance of laureates quite well (Fig. S12).

S4.5 Parameters of the generative hot-streak model

In the main text, the solid lines of Figs. 2i-k show the simulation results of the distribution of the longest streak within a career before the Prize. In this section, we introduce how the simulation results are generated through a simple hot-streak model. Referring to the previous study², we use the empirical productivity information for each laureate to generate a work sequence, and the impact of a work is randomly drawn from a normal distribution $N(\Gamma_H, \sigma^2)$ if it is produced during the hot streak period, or $N(\Gamma_0, \sigma^2)$ if otherwise. We randomly pick one work out of the sequence of works if the laureate produced at least five papers before the Prize (we define a hot-streak period as being composed of no less than five papers) as the start of a hot-streak period, and denote its production year as t_\uparrow . We assume Γ_0 , Γ_H , σ and $t_H = t_\downarrow - t_\uparrow$ to be the same for each individual in a domain, and $\Gamma_H = \Gamma_0 + 1$ for simplicity. The value of parameters, Γ_0 , Γ_H , σ , and t_H of the generative hot-streak model in Figs. 2i-k are evaluated partly according to our previous fitting results and partly as a guide by eye, in particular, $\Gamma_0 = 2.9$, $\Gamma_H = 3.9$, $\sigma = 1.1$, and $t_H = 7.9$ for physics; $\Gamma_0 = 3.1$, $\Gamma_H = 4.1$, $\sigma = 0.9$, and $t_H = 9.8$ for chemistry; $\Gamma_0 = 3.0$, $\Gamma_H = 4.0$, $\sigma = 1.1$, and $t_H = 9.1$ for medicine.

S4.6 Number and duration of hot streaks

We measure the number of hot-streak periods for laureates before the Prize (Fig. S13), and find that their careers are characterized by 1.71 hot streaks (1.51 for physics, 1.85 for chemistry, and 1.76 for medicine) on average, whereas the vast majority of scientists experience just one hot streak.

In Fig. 2o in the main text, we measure the duration distribution of the hot-streak period for Nobel laureates, finding that the duration peaks at around 5.2 years. In Figs. S15a-c, we measure the duration distribution of the hot-streak period over the course of entire careers across different disciplines. The duration peaks at around 5.0, 5.2, and 7.5 years for physics, chemistry, and medicine respectively. Dotted lines represent the median hot-streak duration, which is 8, 7, and 9 years for physics, chemistry and medicine respectively. Figs. S14a-c show the relative duration distribution for individuals, where T is the career length. Figs. S14d-f show the relative duration distribution for individuals, where T is the career length of each individual. Dotted lines represent the median relative hot-streak duration, which hovers at around 22%, 20%, and 22% for physics, chemistry and medicine respectively.

S5 Supporting Information for Figure 3

S5.1 Selecting adjacent papers

In Fig. 3c, we created a null model for prize-winning papers by selecting adjacent papers. The procedure for doing so is introduced here in detail. To ensure the feasibility and reliability of the results, we only focus on the laureates' original work, hence all review and note papers are removed. To rule out the temporal effect, we choose the four non-prize-winning papers with the closest publication time (within three years) for each prize-winning paper by the same individual for use as our null model. In Fig. 3d, we also created a null model for joint prize-winning papers for comparison. In that case, we only consider the joint-authored papers, and for each joint-authored prize-winning paper, we choose 4 joint-authored non-prize-winning papers published by the same Nobel laureate with the closest publication time as the null model.

The same procedure for selecting adjacent papers is also used to build a null model for the hit works (ranked by 10-year citations) to use in comparison when analyzing team size and authorship. When it comes to hit works, it is worth noting that we only focus on papers published before 2005 to ensure that all analyzed papers garner 10-year citations.

S5.2 Authorship analysis controlling for temporal factors

To check if the authorship pattern documented in Fig. 3d is dominated by a temporal effect, we control for publication time and age information using a logistic regression model. The logistic regression model is defined as follows:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \varepsilon_i,$$

where p_i indicates the probability of paper i having the laureate as the first author; x_{i1} is a dummy variable, $x_{i1} = 1$ if paper i is a prize-winning paper, $x_{i1} = 0$ if otherwise; x_{i2} is the publication year of paper i ; and x_{i3} denotes the career age of the laureate when publishing paper i . For each joint-authored prize-winning paper, we choose four joint-authored non-prize-winning papers published by the same Nobel laureate with the closest publication time. We find that the results are robust after controlling for temporal effect, which supports our conclusion that laureates are more likely to claim first authorship in the case of their prize-winning papers (p -value $< 10^{-3}$).

S5.3 Authorship analysis for hit works

We have studied the authorship of all joint prize-winning papers in Fig. 3d, finding that prize-winning papers are substantially more likely to be first-authored by laureates. To test if this phenomenon is unique to the prize-winning work, we repeated the same analysis for each laureate's top three most-cited papers before the Prize by comparing them with those published by the same laureates immediately before and after. First, we compared the proportion of first-authored papers of joint most-cited papers to a null model. For each joint-authored most-cited paper, we choose four joint-authored papers published by the same Nobel laureate with the closest publication time and used these for the null model. While we find that a laureate is more likely to have first-authored her most-cited paper, the phenomenon for the second and third most-cited papers in terms of different disciplines is pretty weak (Figs. S15a-c). It is worth noting that 51.74% of the laureate's most-cited papers are also his/her prize-winning papers. To test if this phenomenon is driven by the recognition that comes with prize-winning work, we repeated our measurements by removing the careers of laureates who published their prize-winning work, and find no statistical difference for physics and medicine, while the difference still holds for chemistry (Figs. S15d-f).

S6 Supporting Information for Figure 4

S6.1 Hit paper rate changes after the Prize

How does a laureate's hit paper rate change after a Prize is awarded? To answer this question, we first measure the top 1% hit paper rate as a function of career years, with the year the Prize is given marked as 0. For each laureate we calculate the top 1% hit paper rate of papers she published in each of the four years before and after the Nobel, as well as those in the prize-winning year. Then, we calculate the average top 1% hit paper rate across all laureates in our sample. We find that the average top 1% hit paper rate remains almost the same—around 17% four years before the Prize. It shows a significant drop in the subsequent two years after the Nobel is awarded, reaching 12%, and then increases slightly by year four. (Fig. S16a). We also measure changes in the

average top 5% hit paper rate after the Prize is awarded. It also experiences a significant drop in the two years after the Nobel, with a slight increase by year four. (Fig. S16b).

S6.2 Robustness check of disciplines

To study if the Nobel dip effect occurs in different disciplines, we calculate the average impact of papers published by the laureates in each of the four years before and after winning the Nobel across three domains. We find that the Nobel dip is most pronounced for prizewinners in physics, who show a reduced impact of 18.1% the second year after the Prize, compared with 4.8% for chemistry and 13.4% for medicine, where prizewinners experiences their most significant dip in the third and first year respectively (Fig. S17). In all domains, the prizewinners' impact gradually recovers, bouncing back to a pre-Nobel level by year four. However, there is no significant difference when it comes to the laureate's productivity before and after the Prize (Fig. S18).

S6.3 Robustness check of publication time

Nobel dip rate, denoted as R in our study, is defined as follows:

$$R = \frac{\langle \Gamma_N \rangle_{after} - \langle \Gamma_N \rangle_{before}}{\langle \Gamma_N \rangle_{after}},$$

where $\langle \Gamma_N \rangle_{before}$ is the average impact of papers two years before winning the Nobel Prize, while $\langle \Gamma_N \rangle_{after}$ measures the average impact of papers two years after winning the Nobel Prize.

To check if our results hold over time, we measure the Nobel dip rate according to each decade in the last century (we merge the first 30 years of the last century into one group because of the small amount of data in the sample). The average impact of papers shows a significant drop in the two years immediately following the Nobel, and the results are robust with respect to different time periods (Fig. S19).

S6.4 Nobel dip after controlling for the burst

The burst of citations to pre-Prize paper may account for part of the observed Nobel dip. Yet more interestingly, we find that the dip persists after we control for the burst. More specifically, we re-measure the paper impact based on citations received within an observation window k , i.e., k years of publication. The impact of paper i , is quantified by $\Gamma_i = \log(\hat{C}_{k,i} + 1)$, where $\hat{C}_{k,i}$ measures the rescaled number of citations within k years of publication. For each laureate, the average impact of papers published in the j th year after Prize is defined as $\langle \Gamma \rangle_j = \frac{\sum_{i=1}^{N_j} \Gamma_i}{N_j}$, where N_j is the number of papers published in the j th year. Given an observation window k , we exclude all works where the impact measure includes post-Prize citations for the pre-Nobel papers and compare the impact of works published in the k th years before and each of the years after winning

Prize. In the main text, we set the observation window as 5 years, and here we alter the observation window as 4 years, 3 years and 2 years. Then we calculate the average impact per paper as a function of publication year with the different observation, we find the average impact per paper still shows a significant drop the year following the Nobel even after excluding works where the impact measure includes post-Prize citations. (Figs. S20a-c).

S6.5 Topic changing after winning the Nobel Prize

To quantify the topic of a paper, we adopt a recent method based on community structure of the co-citing network of a scientist's papers⁴¹. To ensure meaningful community detection results, we consider all Nobel laureates who have published at least 50 papers. We also excluded Nobel laureates who published fewer than five papers after winning the Prize. Finally, we selected 283 Nobel laureates (74 for physics, 96 for Chemistry, 113 for medicine) who satisfied these requirements.

In the main text (Fig. 4h), we measure the probability of two papers belonging to the same topic within 4 years before and after the reception of the Prize and a random year. To measure the probability of changing topics of Nobel laureates after winning Prize, we randomly selected two papers, within 4 years before and after the Nobel, respectively, and measured the probability of two papers belonging to the same topic. We then build a null model by randomly choosing a year as the pretended prize-winning year for comparison.

To ask if Nobel laureates tend to study a new topic after winning Prize, we then measure the chance of Nobel laureates shifting to a new topic after winning the Nobel, $\frac{\#new\ topics\ after\ winning\ Prize}{\#topics}$. We also shuffled the topic of the works and repeated the measurement as a null model for comparison.

S6.6 Topic identification based on Infomap algorithm

In the main text (Fig. 4), we find that laureates disproportionately shift research topic after winning the Nobel. To test if the results are affected by the choice of different community detecting methods, we repeated the results based on another algorithm, Infomap⁴². Figure S21 visualizes the publication history of Nobel laureate Jean-Marie Lehn by color coding each paper according to the topic community to which it belongs. Based on the Infomap community detecting algorithm, the papers of Nobel laureate Jean-Marie Lehn are divided into 17 different communities of topics with 7 starting before the Nobel and 10 starting after (including the Noble year) the Nobel.

We then measured measure the probability of changing topics of Nobel laureates after winning Prize based on the Infomap community detecting method, finding only 42.3% of the two papers belonging to the same topic after winning the Prize. We further build a null model by randomly choosing a year as the pretended prize-winning year for comparison, finding that the probability is significant higher (48.5% vs 42.3%, p -

value=0.03, Fig. S22), which suggests Nobel laureates tend to shift research topic after winning the Nobel.

We also measured the chance of Nobel laureates shifting to a new topic after winning the Nobel based on the Infomap community detecting method, finding the laureates have more than one quarter chance of shifting to a new topic after winning the Nobel. However, the chance is only around 5.0% when we shuffled the topic of the works and repeated the measurement as a null model (25.1% vs 5.0%, p -value $<10^{-12}$, Fig. S23).

S6.7 The popularity of research topics before and after the Prize

To test if the overpopulation of prior topics might encourage laureates to change research agenda after the Nobel, we first focus on laureates' papers that belong to the topics recognized by the Nobel and use citations to these papers as a proxy to trace topic popularity. We find that papers of the prior topics receive much higher citation counts after the Prize than before (Fig. S24, Student's t -test, p -value = 0.04). We then compared the total citation counts of the prior topics before the Prize and those of the new topics after the Prize. We find that the former received higher citations than the latter (Kolmogorov-Smirnov test, p -value $< 10^{-71}$, Fig. 4j in the main text).

While it's difficult to measure directly whether a topic is over-popular, these results suggest that (1) the prior topic continues to be popular after the Nobel; (2) papers published on the Nobel topic tend to garner more citations than papers on the new topic. Together these results are consistent with an endogenous shift by the laureates to explore new directions, even though the new topic may be less popular (less cited on average) than the Nobel topic.

S6.8 Changes in collaborators before and after the Prize

Another rather insightful mechanism is that the Nobel may attract new collaborations, which may be related to the topic change observed following the Nobel. To test this hypothesis, we first compare the number of new collaborators before and after the Prize. We find there is no significant change in the number of new collaborators before and after the Prize (Fig. S25), a pattern that is consistent across all three domains.

Although the number of new collaborators did show any significant change, the Nobel with added recognition may attract more established collaborators. To test this hypothesis, we analyzed the publication record of the collaborators before and after the Nobel. For each collaborator, we only focus their career record before the first collaboration with the laureate. We define N_k as the number of papers published before the first collaboration with Nobel laureates for collaborators k , and the impact of collaborators k is measured as $\Gamma_k = \log(\sum_{i=1}^{N_k} C_{10,i} + 1)$, where $C_{10,i}$ is the 10-year citation counts of paper i . Comparing the profiles of collaborators before and after the Nobel, we find post-Prize collaborators tend to be more productive (Student's t -test, p -value $< 10^{-3}$, Fig. 4k in the main text) and have a higher impact (Student's t -test, p -value = 0.02, Fig. 4l in the main text).

Together, these results suggest that the Nobel does not necessarily attract more new collaborators than expected, but new collaborators after the Nobel tend to be more productive with higher impact. From this result, one would expect the impact of works produced after the Nobel to increase, not decrease, which then makes the impact dip shortly after the Nobel more intriguing.

S6.9 Funding opportunities before and after the Prize

The Prize and the added recognition may result in more and better funding opportunities, conducive to changing research directions. To test this hypothesis, in this revision we have acquired a novel dataset that captures funding records across all funding agencies world-wide, linked with individual investigators and resulting publications⁴³⁻⁴⁷. To the best of our knowledge, it is the most comprehensive research grants database to date⁴⁸, ideal to test this hypothesis.

We collected around 5 million grants between 1950 and 2019. We then connect the grant records to the careers of Nobel laureates we curated through systematic efforts of paper matching and author name disambiguation, resulting in 470 grants for 51 Physics laureates, 920 grants for 66 Chemistry laureates, and 509 grants for 72 Medicine laureates, respectively.

To measure changes in funding opportunities before and after the Prize, we first compare the average number of active grants for each laureate in each of the four years before and after winning the Nobel, finding that overall there is no significant change (Fig. S26a). We then separated this measurement by field, finding a suggestive signal for Physics laureates to increase their grant support around the time of the award (Fig. S26b), whereas the active grants for Chemistry and Medicine laureates stayed roughly the same (Figs. S26cd). We also compare the average number of new grants within four years before and after winning the Nobel, arriving at the same conclusion (Fig. 4m in the main text). Together our analysis suggests that there is no significant change in funding before and after the Prize, which is somewhat surprising. Indeed, according to the Matthew effect, we would have expected to observe an increase in funding. On the other hand, the lack of increase is consistent with the change in topic and research agenda which requires more time to build up for funding.

S7 Supplementary Figures

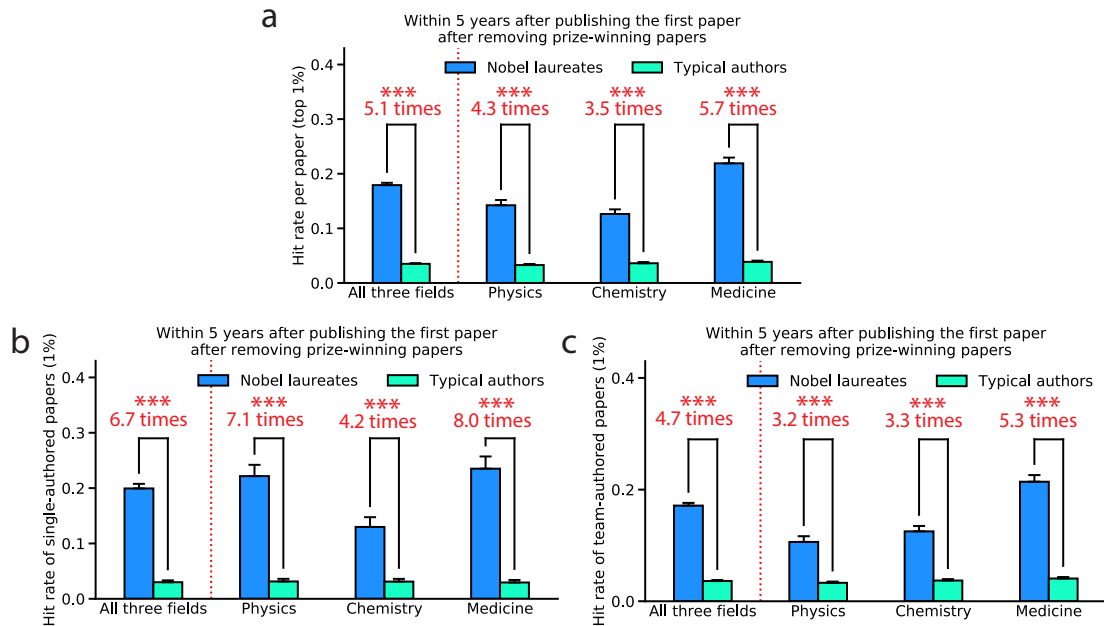


Fig. S1 | Hit paper rate (top 1%) after removing the prize-winning paper. A comparison of hit paper rate (top 1%) for Nobel laureates and typical authors in terms of all papers (a), single-authored papers (b), and joint papers (c). Even after removing prize-winning papers, both Nobel laureates' early-stage single-authored papers and joint-authored papers have much higher impact in terms of the hit paper rate (top 1%). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and NS for $p > 0.1$. Error bar represents the standard error of the mean.

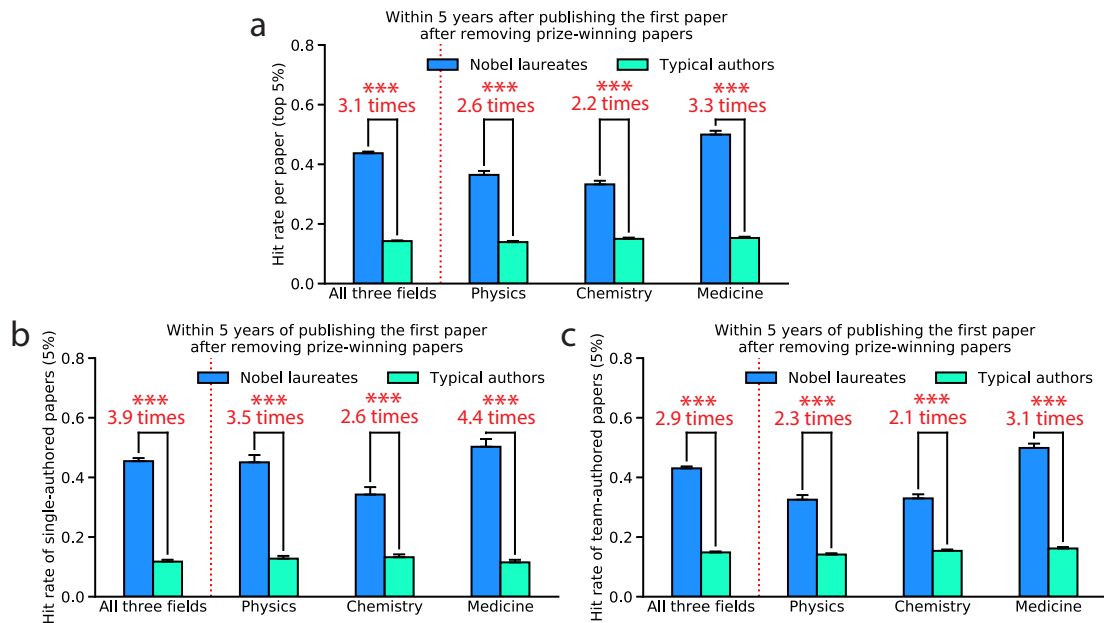


Fig. S2 | Hit paper rate (top 5%) per early-stage paper after removing prize-winning paper. A comparison of hit paper rate (top 5%) for Nobel laureates and typical authors in terms of all papers (a), single-authored papers (b), and joint papers (c). Even after removing prize-winning papers, both Nobel laureates' early-stage single-authored papers and joint-authored papers have much higher

impact in terms of the hit paper rate (top 5%). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and NS for $p > 0.1$. Error bar represents the standard error of the mean.

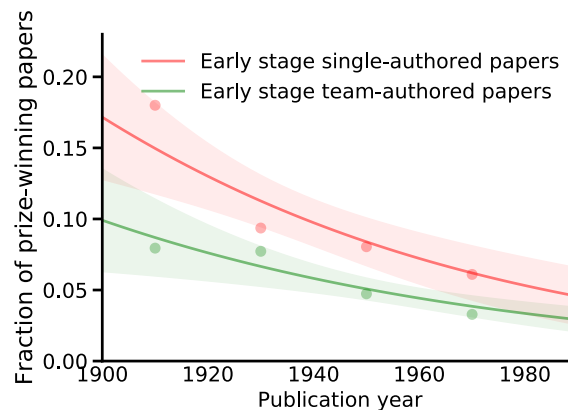


Fig. S3 | Proportion of early-stage prize-winning papers as a function of publication time. The average fraction of early-stage prize-winning papers decreases over time, which is well-fitted using a logistic regression model. The scattered data points refer to the mean value averaged within 20 years and shading around the lines shows 95% confidence limits. In the early-stage, after controlling for publication year, we also find that single-authored papers have a higher probability of being prize-winning than team-authored papers (p -value $< 10^{-3}$).

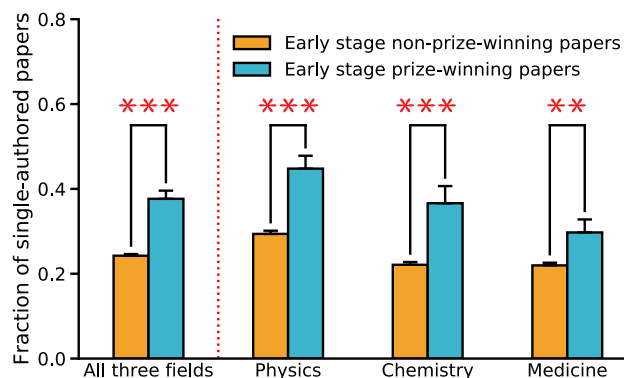


Fig. S4 | Fraction of single-authored papers in the early stage. We compare the fraction of single-authored papers within all laureates' early stage non-prize-winning papers (orange) and within prize-winning papers published in early stages (green) for the entire group of laureates that we examined. The fraction of single-authored papers is much higher among early-stage prize-winning papers than for non-prize-winning papers in the early stage, a trend that holds for physics, Chemistry, and medicine. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and N.S. (not significant) for $p > 0.1$. Error bars represent the standard errors of the mean.

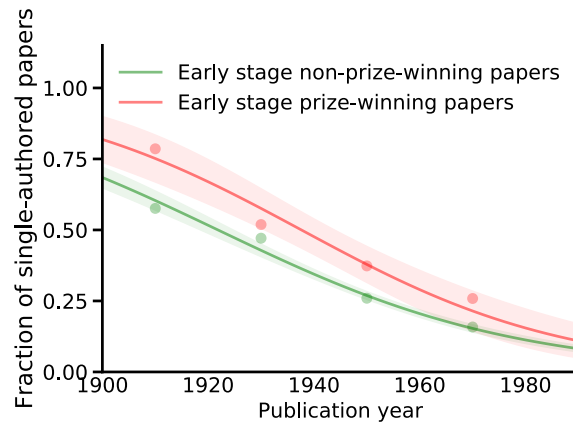


Fig. S5 | Proportion of single-authored early stage papers as a function of publication time.

The average fraction of single-authored early stage papers decreases over time, which is well-fitted using a logistic regression model. The scattered data points refer to the mean value averaged within 20 years and shading around the lines shows 95% confidence limits. After controlling for the publication year, we find that early-stage papers are more likely to be single-authored (p -value $< 10^{-3}$).

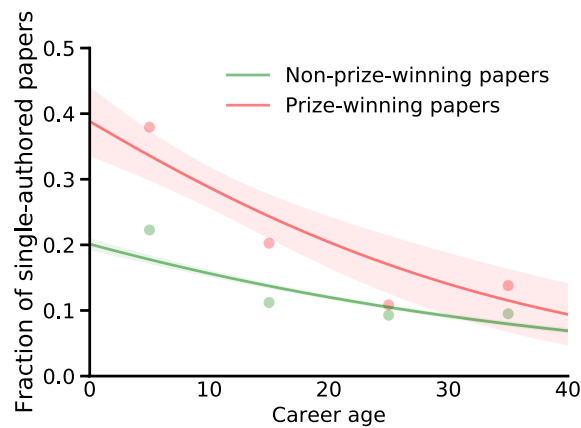


Fig. S6 | Proportion of single-authored papers as a function of career age.

The average fraction of single-authored papers decreases over career age, which is well-fitted using a logistic regression model. The scattered data points refer to the mean value averaged within 10 career years and shading around the lines shows 95% confidence limits. The fraction of single-authored papers is much higher among prize-winning than non-prize-winning papers in the early stage, though the advantage of single-authoring decays systematically over time, reaching a balance point after roughly 30 years, when prize-winning papers have relatively the same chance of being single-authored or team-authored.

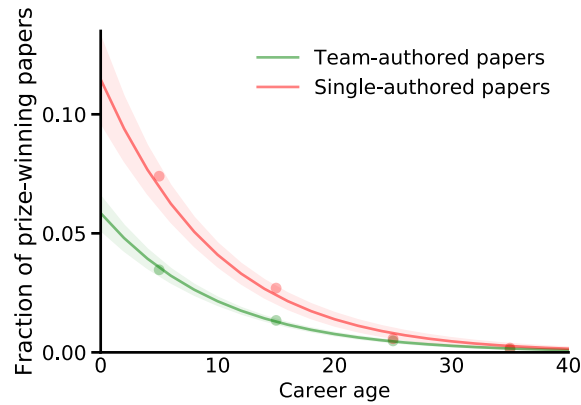


Fig. S7 | Proportion of prize-winning papers as a function of career age. The average fraction of prize-winning papers decreases over career age, which is well-fitted using a logistic regression model. The scattered data points refer to the mean value averaged within 10 career years and shading around the lines shows 95% confidence limits. Single-authored papers have a higher chance of being prize-winning in the early stage, though the advantage of single-authoring decays systematically over time, reaching a balance point after roughly 30 years, when single-authored and team-authored papers have relatively even odds of being prize-winning.

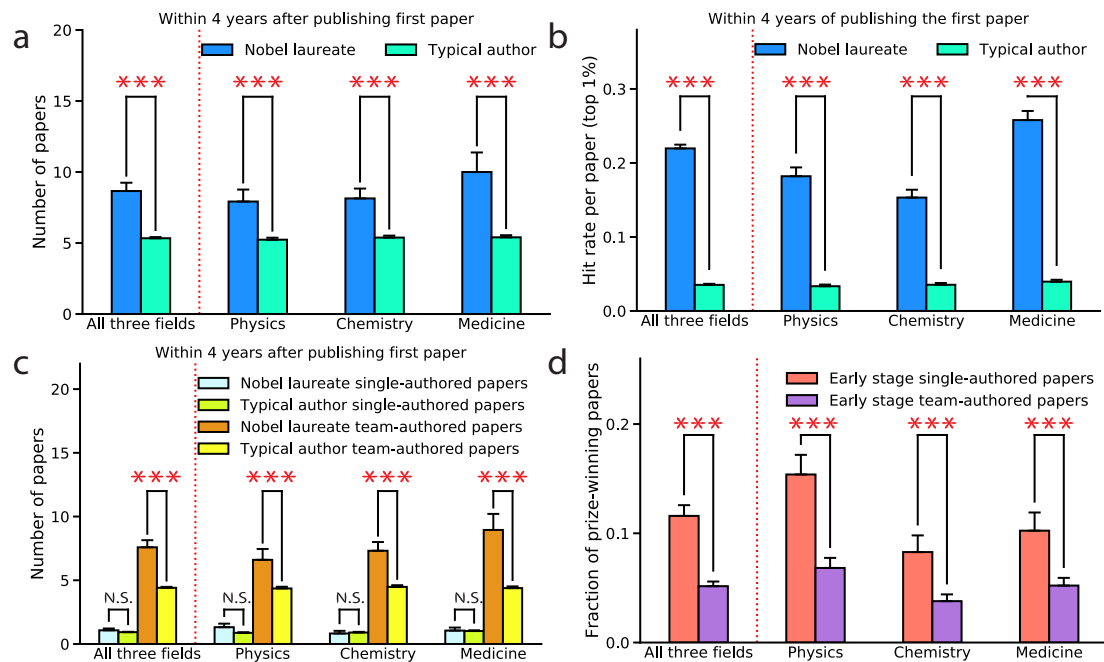


Fig. S8 | Early Career Performance (The First Four Years). **a** In terms of productivity, the Nobel laureates are indeed more prolific (8.66 vs 5.34, Student's t-test, p -value $< 10^{-7}$). **b** When it comes to impact, the two populations are not comparable, and the hit paper rate (top 1%) of the Nobel laureates is 6.23 times higher than for typical authors. **c** Much of the difference in early published output between Nobel laureates and typical scientists resulted from joint papers (7.59 vs 4.41, Student's t-test, p -value $< 10^{-7}$). There was no significant difference between the average number of single-authored papers published by laureates in their early stage and the average author. **d** We further compare the fractions of prize-winning papers within all laureates' early stage single-authored papers and within team-authored papers published in early stages. The fraction of prize-

winning papers is much higher among early-stage single-authored papers than for team-authored papers (Chi-squared test, p -value $<10^{-11}$). *** $p<0.01$, ** $p<0.05$, * $p<0.1$ and N.S. (not significant) for $p>0.1$. Error bars represent the standard errors of the mean.

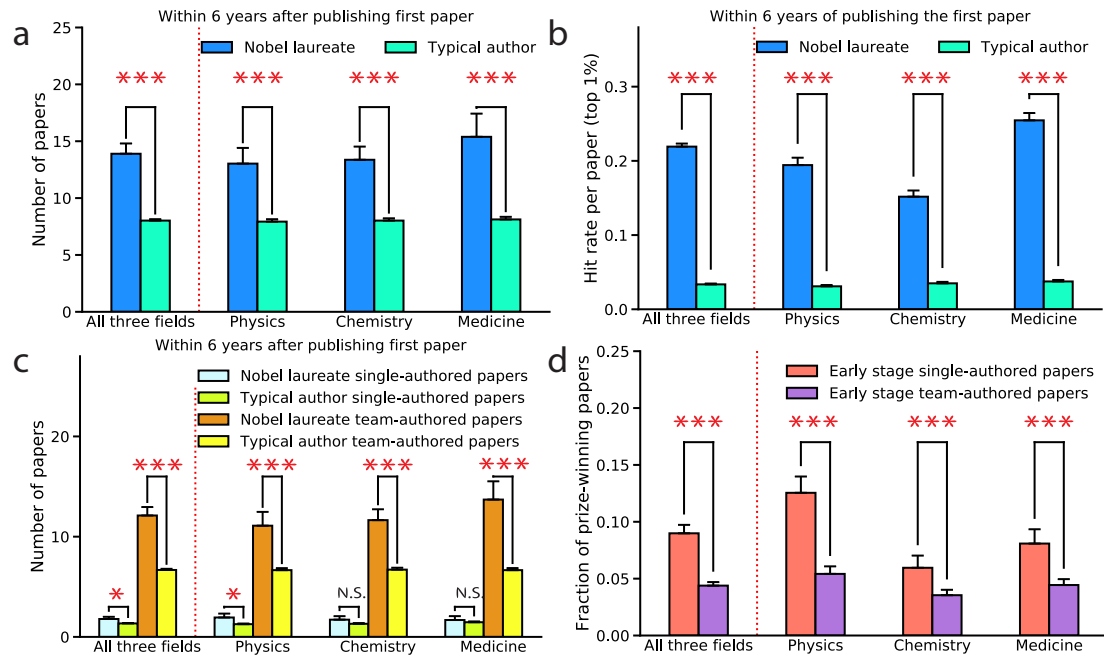


Fig. S9 | Early Career Performance (The First Six Years). **a** In terms of productivity, the Nobel laureates are indeed more prolific (13.90 vs 8.02, Student's t-test, p -value $<10^{-8}$). **b** When it comes to impact, the two populations are not comparable, and the hit paper rate (top 1%) of the Nobel laureates is 6.53 times higher than for typical authors. **c** Much of the difference in early published output between Nobel laureates and typical scientists resulted from joint papers (12.11 vs 6.68, Student's t-test, p -value $<10^{-8}$). In chemistry and medicine, there was no significant difference between the average number of single-authored papers published by laureates in their early stage and the average author. In physics, Nobel laureates tend to publish more single-authored papers than typical authors (Student's t-test, p -value=0.09). **d** We further compare the fractions of prize-winning papers within all laureates' early stage single-authored papers and within team-authored papers published in early stages. The fraction of prize-winning papers is much higher among early-stage single-authored papers than for team-authored papers (Chi-squared test, p -value $<10^{-10}$). The difference is significant for laureates in physics and Chemistry, but we find no significant difference for laureates in medicine. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ and N.S. (not significant) for $p>0.1$. Error bars represent the standard errors of the mean.

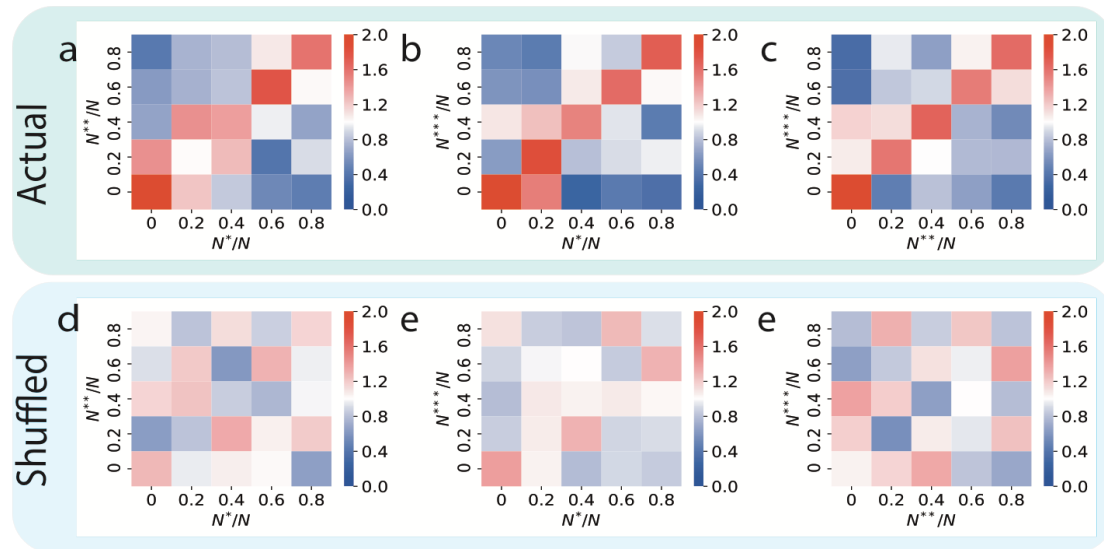


Fig. S10 | Joint probability of the top three highest impact works. **a-c** We measure the joint probability of the top three highest impact works within a career before the Prize. Values greater than 1 indicate two hits are more likely to collocate than random. **d-f** We shuffle the order of each work in a career while keeping their impacts intact as a null model for **a-c**. We find clear diagonal patterns, demonstrating that high-impact papers are more likely to cluster together than expected by chance. The diagonal pattern disappears when we shuffle the order of the works.

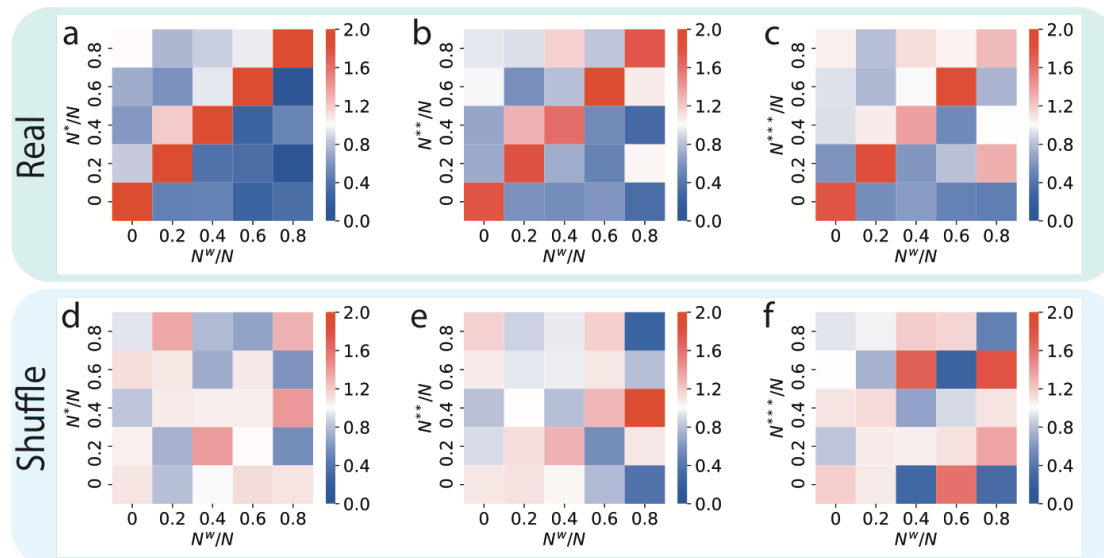


Fig. S11 | Joint probability of prize-winning papers and the top three highest impact works. **a-c** We measure the joint probability of a prize-winning paper (for Nobel laureates with multiple prize-winning papers, we take the average; the same below) and the top three highest impact works within a career before the Prize. Values greater than 1 indicate two hits are more likely to collocate than random. **d-f** We shuffle the order of each work in a career while keeping their impact intact as a null model for **a-c**. We can find a clear positive correlation between prize-winning papers and the top three highest impact works along the diagonal.

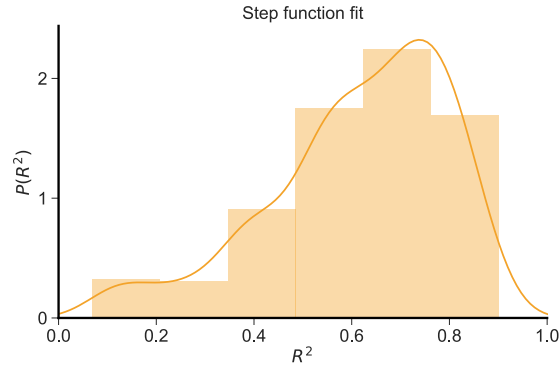


Fig. S12 | The distribution of the coefficient of determination R^2 . We fit each laureate’s career performance using the hot-streak model, and measure the R^2 between the step-function-simulated careers and the real careers of all Nobel winners in our dataset. We find the R^2 peaks around 0.75, suggesting the hot-streak model captures the career performance of laureates well.

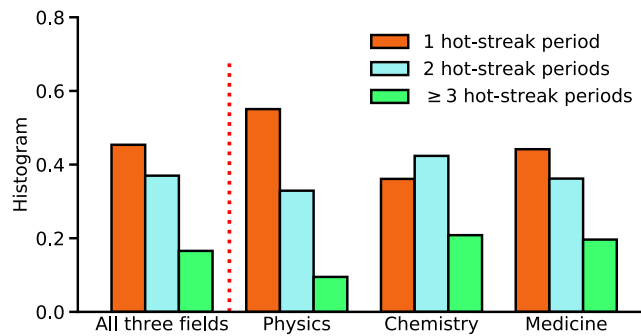


Fig. S13 | Histogram of the number of hot-streak periods before the Prize. Laureates in all three Nobel fields experience 1.71 hot-streak periods on average (1.51 for physics, 1.85 for chemistry and 1.76 for medicine).

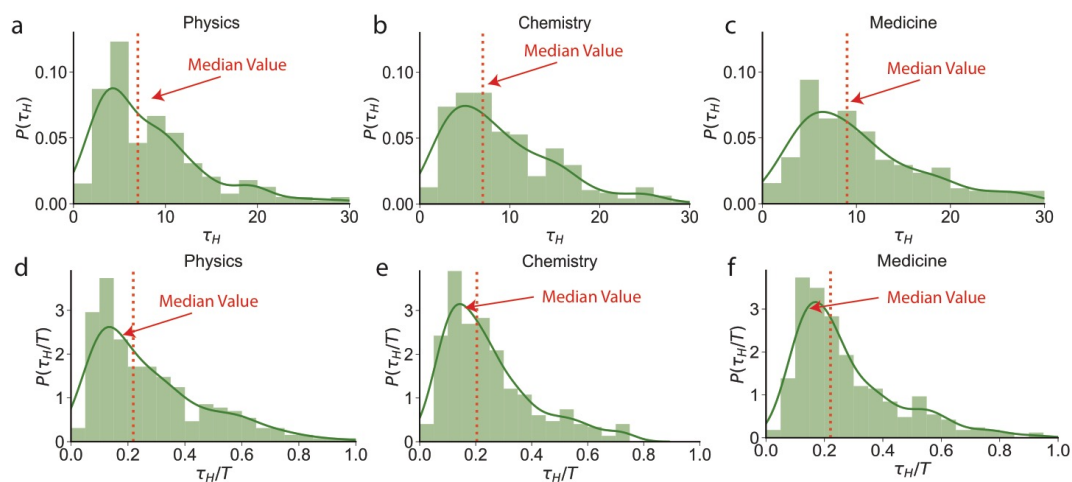


Fig. S14 | Hot-streak duration distribution across different disciplines. **a-c** We measure the duration distribution of the hot-streak period within careers across different disciplines. The duration peaks at around 5.0, 5.2 and 7.5 years for physics, chemistry and medicine respectively. Dotted lines represent the median hot-period duration, which is 8, 7, and 9 years for physics, chemistry and medicine respectively. **d-f** We shows the relative duration distribution for individuals, where T is

the career length of each individual. Dotted lines represent the median relative hot-period duration, which hovers around 22%, 20% and 22% for physics, chemistry and medicine respectively.

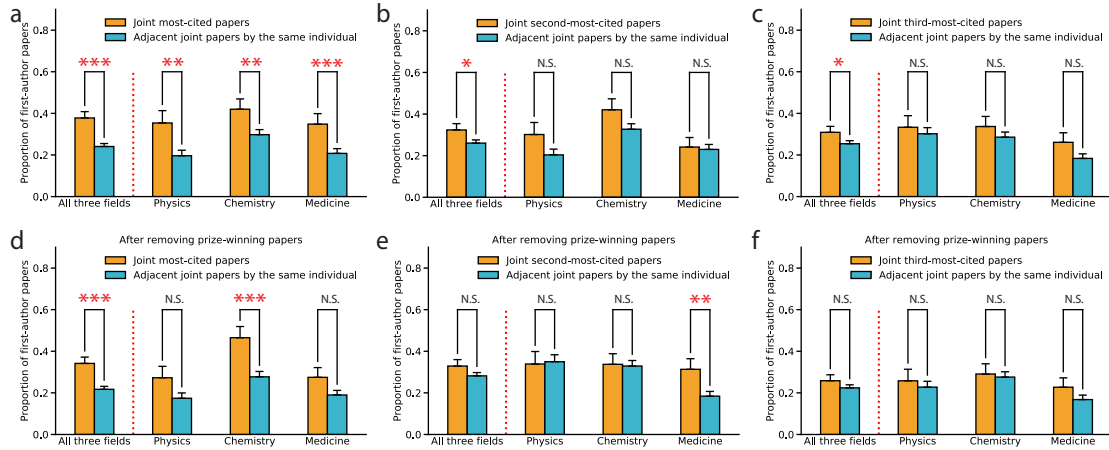


Fig. S15 | Fraction of first-authored papers of joint hit works. We calculate the laureates’ fraction of first-authored papers of joint hit works before the Prize (**a** for most-cited papers, **b** for second-most-cited papers, and **c** for third-most-cited papers) in comparison with a null model. In this case, we only consider joint-authored papers. For each joint-authored hit work, we choose four joint-authored papers published by the same Nobel laureate with the closest publication time as the null model. To rule out the effect of the prize-winning works, we repeated our measurements by removing the careers of laureates who published their prize-winning work (**d** for most-cited papers, **e** for second-most-cited papers, and **f** for third-most-cited papers). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and N.S. (not significant) for $p > 0.1$. Error bars represent the standard errors of the mean.

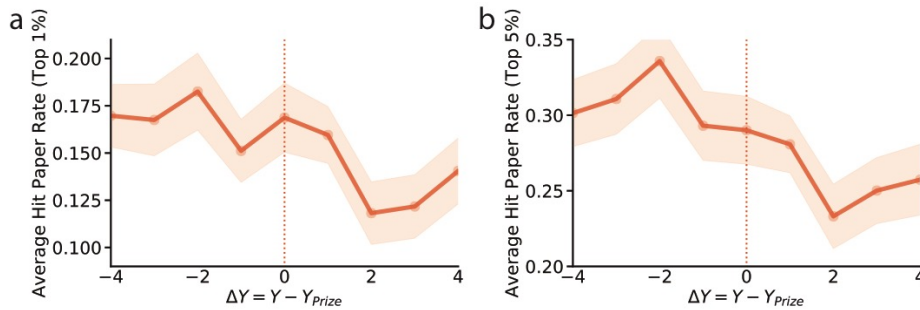


Fig. S16 | Average hit rate of papers published four years before and after the Nobel Prize year. **a** The solid line indicates the average across all papers in our sample, with the shaded area denoting the standard error of the mean. We find that the average top 1% hit paper rate remains almost the same--roughly 17%--four years before the Prize, then shows a significant drop in the subsequent two years after the Nobel is awarded, reaching 12%, and then slightly increasing by year four. **b** We also measure the average top 5% hit paper rate change before and after the Prize, which likewise experiences a significant drop in the two years after the Nobel is awarded and a slight increase by year four.

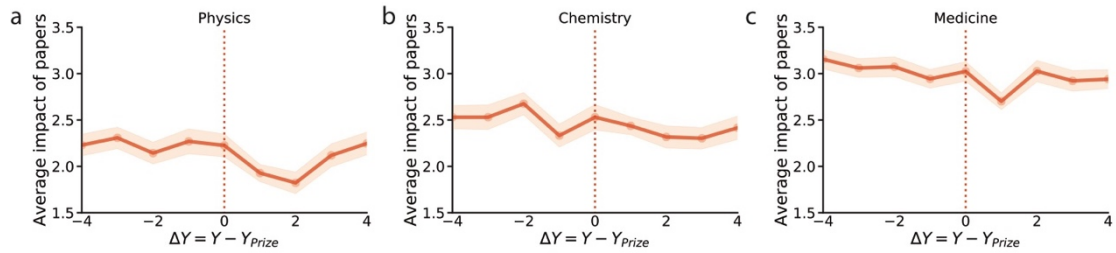


Fig. S17 | Impact of papers published four years before and after the Nobel Prize year according to different disciplines. The solid line indicates the average across all laureates in our sample, with the shaded area denoting the standard error of the mean. The Nobel dip is most pronounced in physics, where laureates show a reduced impact of 18.1% in the second year after the Prize, compared with a drop of 4.8% in chemistry and 13.4% in medicine. In chemistry and medicine, laureates experience their most significant dip in the third and first year respectively.

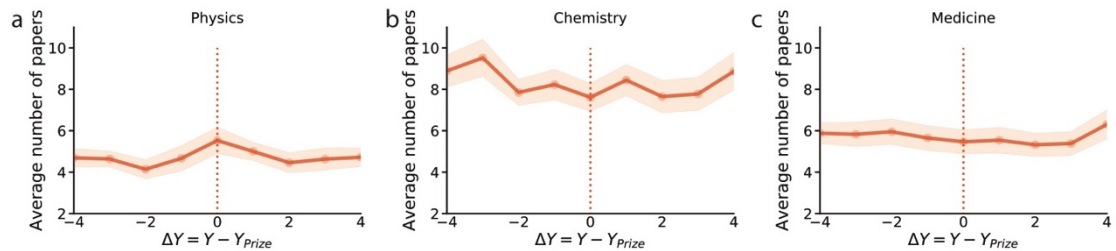


Fig. S18 | Average number of papers published four years before and after the Nobel Prize year according to different disciplines. The solid line indicates the average across all laureates in our sample, with the shaded area denoting the standard error of the mean. In all three disciplines, productivity does not drop significantly after the Nobel is awarded.

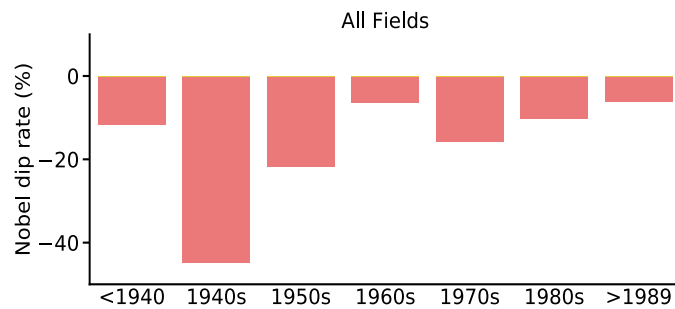


Fig. S19 | Nobel dip rate according to different time periods (two years before and after winning Nobel Prize). The average paper impact per paper shows a significant drop in the two years immediately following the Nobel, and these results are robust with respect to different time periods.

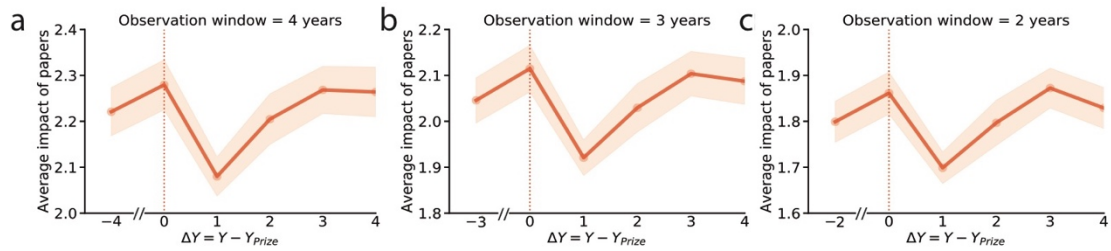


Fig. S20 | Average impact per paper as a function of career years. **a** We set the observation window as 4 years and calculate the average impact of papers based on the 4-year citation counts. For each laureate, we exclude all works where the impact measure includes post-Prize citations and compare the average impact of papers published by the laureates in the 4th year before and each of the four years after winning the Nobel. The solid line indicates the average across all laureates in our sample four years before and after the Nobel, as well as the prize winning year, with the shaded area denoting the standard error of the mean. **b-c** Average impact per paper as a function of career years with the observation windows as 3 years and 2 years respectively.

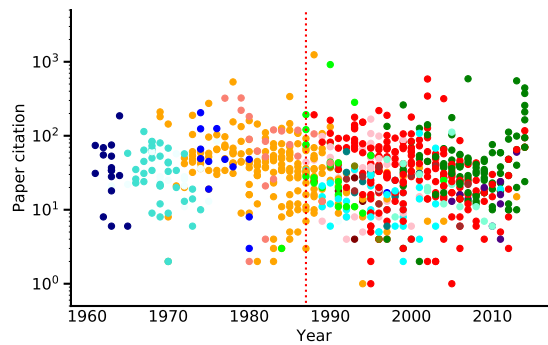


Fig. S21 | The publication history of Nobel laureate Jean-Marie Lehn by color coding each paper according to the related topic community based on the Infomap community detecting algorithm. The X-axis shows the time series of all the papers published by Nobel laureate Jean-Marie Lehn, and the Y-axis shows the citation for each paper. Each paper is represented by a point and the color corresponds to the topic community in the co-citing network.

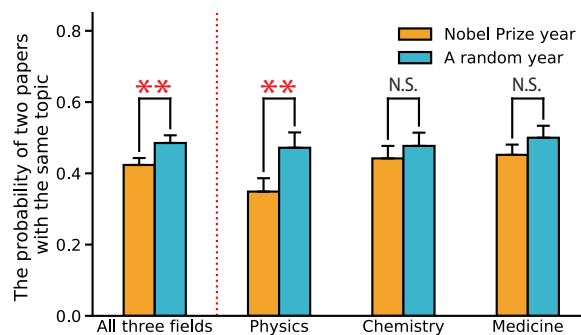


Fig. S22 | Comparison of the probability of two papers belonging to the same topic within 4 years before and after the reception of the Prize and a random year. The probability is significant lower after winning the Prize, suggesting Nobel laureates tend to shift research topic

after winning the Nobel. The change is significant for physics, while there is no significant difference for chemistry and medicine. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and N.S. (not significant) for $p > 0.1$. Error bars represent the standard errors of the mean.

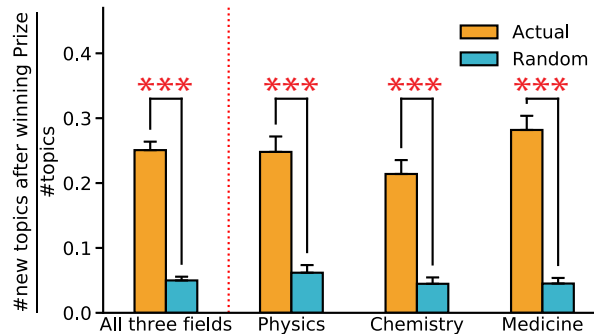


Fig. S23 | Comparison of the likelihood of laureates shifting to a new topic after winning Prize with random. We measured the likelihood of laureates shifting to a new topic after winning Prize, $\frac{\#new\ topics\ after\ winning\ Prize}{\#topics}$. Then, we shuffled the topic of the works and repeated the

measurement as a null model, finding that the laureates are much more likely to shift to a new topic after winning Prize than random. The observation is significant for all three fields. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and N.S. (not significant) for $p > 0.1$. Error bars represent the standard errors of the mean.

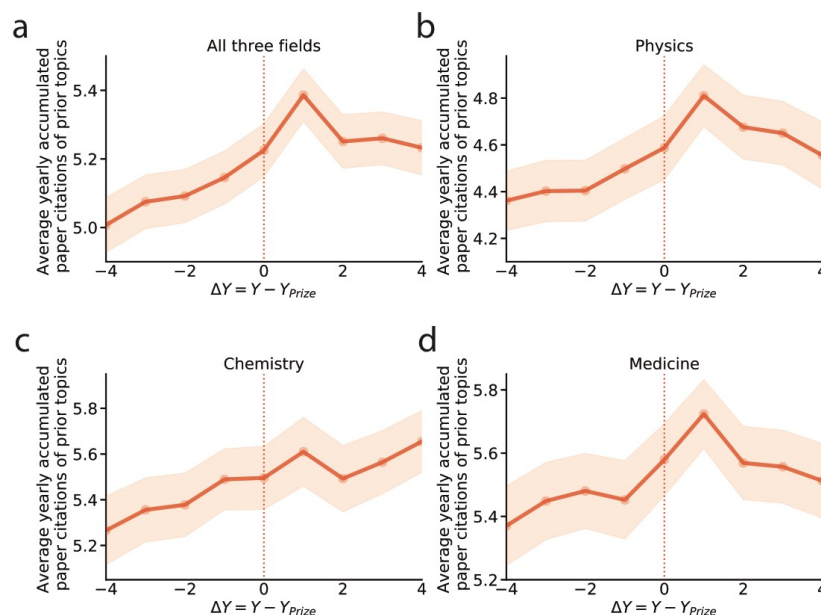


Fig. S24 | Average yearly accumulated citation counts of prior topic papers as a function of career years. We focus on laureates' papers that belong to the prior Prize topics, and measure its yearly accumulated citation counts before and after the Prize. The solid line indicates the average across all laureates in our sample four years before and after the Nobel, as well as the prize winning year, with the shaded area denoting the standard error of the mean.

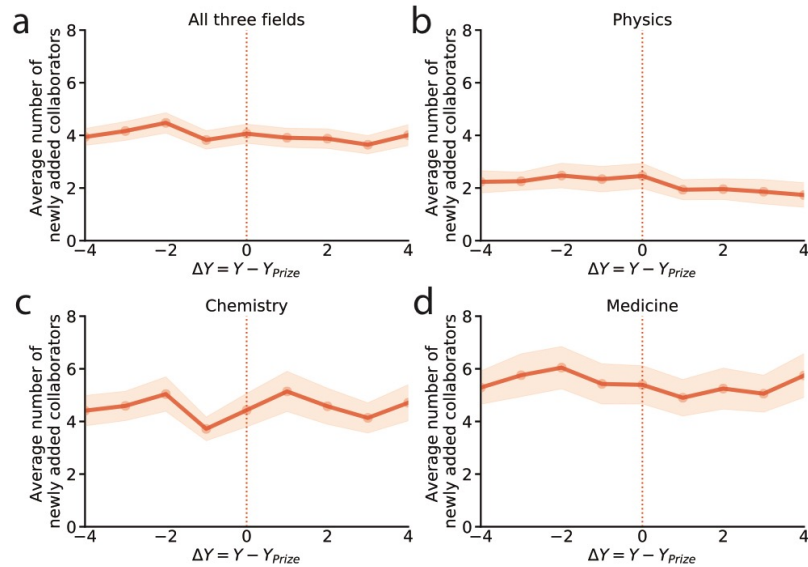


Fig. S25 | Average number of new collaborators before and after the Prize. For each laureate, we calculate the new collaborators each year. The solid line indicates the average across all laureates in our sample four years before and after the Nobel, as well as the prize-winning year, with the shaded area denoting the standard error of the mean.

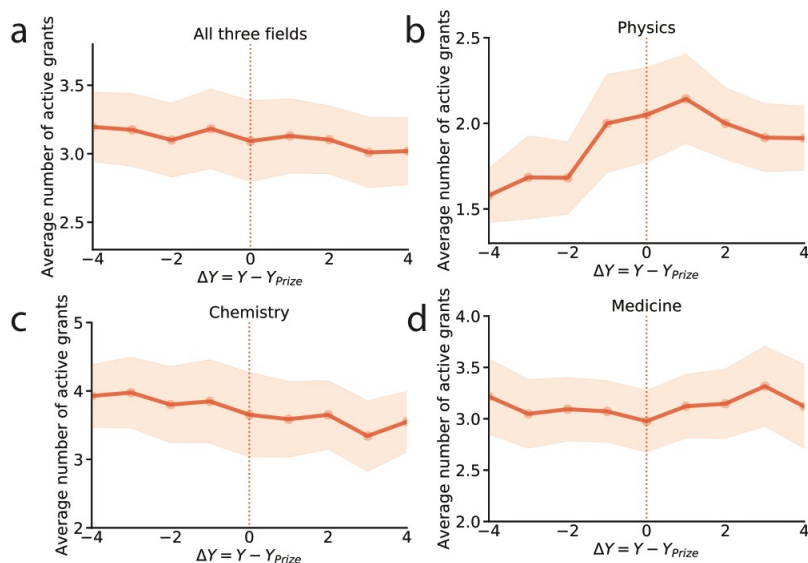


Fig. S26 | Funding opportunities changing before and after the Prize. a-d Average number of active grants as a function of career years. We only focus on those laureates who participated in at least one active grant project both within 5 years before and after the Prize, thus resulting in 25 Physics laureates, 46 Chemistry laureates and 43 Medicine laureates. The year when the Prize is given is marked as 0. For each laureate, we calculate the active grant number he/she involved in each of the four years before and after the Nobel, as well as the prize-winning year. The solid line indicates the average across all laureates in our sample, with the shaded area denoting the standard error of the mean.

Reference

- 1 Li, J., Yin, Y., Fortunato, S. & Wang, D. A dataset of publication records for Nobel laureates. *Sci Data* **6**, 33 (2019).
- 2 Liu, L. *et al.* Hot Streaks in Artistic, Cultural, and Scientific Careers. *Nature* **559**, 396–399, <https://doi.org/10.1038/s41586-018-0315-8> (2018).
- 3 Jones, B. F. & Weinberg, B. A. Age dynamics in scientific creativity. *P Natl Acad Sci USA* **108**, 18910-18914 (2011).
- 4 Manniche, E. & Falk, G. Age and the Nobel-Prize. *Behav Sci* **2**, 301-307 (1957).
- 5 Zuckerman, H. The sociology of the Nobel prizes. *Sci Am* **217**, 25-+, <https://doi.org/10.1038/scientificamerican1167-25> (1967).
- 6 Zuckerman, H. Nobel laureates in science: Patterns of productivity, collaboration, and authorship. *Am Sociol Rev* **32**, 391-403, <https://doi.org/10.2307/2091086> (1967).
- 7 Zuckerman, H. *Scientific Elite: Nobel Laureates in the United States*. (Free Press, 1977).
- 8 Ashton, S. V. & Oppenheim, C. Method of Predicting Nobel Prizewinners in Chemistry. *Soc Stud Sci* **8**, 341-348, Doi 10.1177/030631277800800306 (1978).
- 9 Elisabeth, C. (Cambridge: Cambridge University Press, 1984).
- 10 Garfield, E. Do Nobel-Prize Winners Write Citation-Classics. *Curr Contents*, 3-8 (1986).
- 11 Diamond, A. M. Citation counts for Nobel Prize winners in economics. *Journal of the History of Economic Thought* **10**, 67-70 (1988).
- 12 MacLachlan, J. Defining physics: the Nobel Prize selection process, 1901–1937. *American Journal of Physics* **59**, 166-174 (1991).
- 13 Garfield, E. & Welljams-Dorof, A. Of Nobel class: a citation perspective on high impact research authors. *Theor Med* **13**, 117-135 (1992).
- 14 Van Dalen, H. P. The golden age of Nobel economists. *The American Economist* **43**, 19-35 (1999).
- 15 Rodgers, P. Countdown to the Nobel prize. *Phys World* **13**, 10 (2000).
- 16 Feldman, B. The Nobel Prize. *A History of Genius, Controversy and Prestige/Burton Feldman*.-New York: Arcade Pub (2000).
- 17 Friedman, R. M. *The politics of excellence: Behind the Nobel Prize in science*. (Times Books, 2001).
- 18 Crawford, E. Nobel population 1901-50: anatomy of a scientific elite. *Phys World* **14**, 31-35 (2001).
- 19 Crawford, E. *Nationalism and internationalism in science, 1880-1939: four studies of the Nobel population*. (Cambridge University Press, 2002).
- 20 James, I. Singular scientists. *J Roy Soc Med* **96**, 36-39, DOI 10.1258/jrsm.96.1.36 (2003).
- 21 Friedman, R. M. Is science losing out in the race for recognition? *Nature* **426**, 495-495, [10.1038/426495a](https://doi.org/10.1038/426495a) (2003).
- 22 Hirsch, J. E. An index to quantify an individual's scientific research output. *P Natl Acad Sci USA* **102**, 16569-16572, [10.1073/pnas.0507655102](https://doi.org/10.1073/pnas.0507655102) (2005).
- 23 Wray, K. B. Scientific authorship in the age of collaborative research. *Stud Hist Philos*

- Sci* **37**, 505-514, 10.1016/j.shpsa.2005.07.011 (2006).
- 24 Rablen, M. D. & Oswald, A. J. Mortality and immortality: The Nobel Prize as an experiment into the effect of status upon longevity. *J Health Econ* **27**, 1462-1471, 10.1016/j.jhealeco.2008.06.001 (2008).
- 25 Gingras, Y. & Wallace, M. L. Why it has become more difficult to predict Nobel Prize winners: a bibliometric analysis of nominees and winners of the chemistry and physics prizes (1901-2007). *Scientometrics* **82**, 401-412, 10.1007/s11192-009-0035-9 (2010).
- 26 Rodríguez-Navarro, A. Measuring research excellence: Number of Nobel Prize achievements versus conventional bibliometric indicators. *Journal of Documentation* **67**, 582-600 (2011).
- 27 Mazloumian, A., Eom, Y. H., Helbing, D., Lozano, S. & Fortunato, S. How citation boosts promote scientific paradigm shifts and nobel prizes. *Plos One* **6**, <https://doi.org/10.1371/journal.pone.0018975> (2011).
- 28 Baffes, J. & Vamvakidis, A. Are you too young for the Nobel Prize? *Res Policy* **40**, 1345-1353, 10.1016/j.respol.2011.06.001 (2011).
- 29 Heinze, T., Heidler, R., Heiberger, R. H. & Riebling, J. New patterns of scientific growth: How research expanded after the invention of scanning tunneling microscopy and the discovery of Buckminsterfullerenes. *J Am Soc Inf Sci Tec* **64**, 829-843, 10.1002/asi.22760 (2013).
- 30 Chan, H. F. & Torgler, B. Time-lapsed awards for excellence. *Nature* **500**, 29-29, <https://doi.org/10.1038/500029c> (2013).
- 31 Azoulay, P., Stuart, T. & Wang, Y. B. Matthew: Effect or fable? *Manage Sci* **60**, 92-109, <https://doi.org/10.1287/mnsc.2013.1755> (2014).
- 32 Liu, Y. X. & Rousseau, R. Citation Analysis and the Development of Science: A Case Study Using Articles by Some Nobel Prize Winners. *J Assoc Inf Sci Tech* **65**, 281-289, 10.1002/asi.22978 (2014).
- 33 Fortunato, S. Prizes: Growing time lag threatens Nobels. *Nature* **508**, 186, <https://doi.org/10.1038/508186a> (2014).
- 34 Wagner, C. S., Horlings, E., Whetsell, T. A., Mattsson, P. & Nordqvist, K. Do Nobel Laureates create prize-winning networks? An analysis of collaborative research in physiology or medicine. *Plos One* **10**, e0134164 (2015).
- 35 Hansson, N., Fangerau, H., Tuffs, A. & Polianski, I. J. No Silver Medal for Nobel Prize Contenders Why Anesthesia Pioneers Were Nominated for but Denied the Award. *Anesthesiology* **125**, 34-38, 10.1097/Aln.0000000000001099 (2016).
- 36 Sondhi, S. & Kivelson, S. Time to fix science prizes. *Nat Phys* **13**, 822-822, DOI 10.1038/nphys4246 (2017).
- 37 Seeman, J. I. Synthesis and the Nobel Prize in Chemistry. *Nat Chem* **9**, 925-929, DOI 10.1038/nchem.2864 (2017).
- 38 Hansson, N., Halling, T. & Fangerau, H. Nobel nomination letters point to a winning formula. *Nature* **555**, 311, <https://doi.org/10.1038/d41586-018-03057-z> (2018).
- 39 Ferry, G. Ribosome reader to Royal Society leader: a biologist's road to the Nobel. *Nature* (2018).
- 40 Weinberg, B. A. & Galenson, D. W. Creative careers: The life cycles of Nobel laureates in economics. *De Economist* **pp**, 1-18 (2019).

- 41 Zeng, A. *et al.* Increasing trend of scientists to switch between topics. *Nature Communications* **10**, 3439 (2019).
- 42 Rosvall, M. & Bergstrom, C. T. Maps of random walks on complex networks reveal community structure. *Proceedings of the National Academy of Sciences* **105**, 1118-1123 (2008).
- 43 Hook, D. W., Porter, S. J. & Herzog, C. Dimensions: building context for search and evaluation. *Frontiers in Research Metrics and Analytics* **3**, 23 (2018).
- 44 Herzog, C., Hook, D. & Konkiel, S. Dimensions: Bringing down barriers between scientometricians and data. *Quantitative Science Studies*, 1-9 (2020).
- 45 Orduna-Malea, E., Aytac, S. & Tran, C. Y. Universities through the eyes of bibliographic databases: a retroactive growth comparison of Google Scholar, Scopus and Web of Science. *Scientometrics* **121**, 433-450 (2019).
- 46 Orduna-Malea, E. & López-Cózar, E. D. Demography of Altmetrics under the Light of Dimensions: Locations, Institutions, Journals, Disciplines and Funding Bodies in the Global Research Framework. *Journal of Altmetrics* **2** (2019).
- 47 Mouratidis, R. W. Dimensions. *Journal of the Medical Library Association: JMLA* **107**, 459 (2019).
- 48 <https://www.dimensions.ai/>.