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The distinctive innovation patterns and network embeddedness of scientific prizewinners

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Science prizes purportedly reward innovation and explorations of new phenomena. Yet in practice, prizes may inadvertently divert resources from similarly impactful but less celebrated scholars. Despite this paradox, and even as prizes proliferate, knowledge of how prizewinning relates to innovation is nascent. Analyzing 2,460 worldwide prizes, we compared the innovativeness of over 23,000 prizewinners and matched nonprizewinners whose performance records were statistically equivalent up to the prize year. First, we find that prizewinners are more innovative. Their research is more likely to combine existing ideas in new ways, integrate a topic's historical and contemporary thinking, and incorporate interdisciplinary perspectives. Second, although prizewinners and matched nonprizewinners have statistically equivalent impact and productivity records up to the prize year, at about five years before the prize, prizewinners' papers become more innovative than their matched peers. This difference widens each year, peaks during the prize year, and then persists for the remainder of their careers. Third, network embeddedness predicts unusual innovativeness. Compared to nonprizewinners, prizewinners' collaborations are shorter in duration, encompass wider exposure to unfamiliar topics, and involve coauthors whose networks minimally overlap with each other. The findings' implications for innovation in science and the efficacy of reward systems and innovation in science are discussed.

innovation | science prizes | Matthew effects | science of science | embeddedness

Science prizewinners disproportionately influence scientific thought, resources, research problems, and policies (1–15). They are celebrated in the media, at conventions, in journals and announcements, and in hallway conversations and nomination letters that highlight a scholar's work and reputation (1, 2, 5, 16–22). Their work is associated with an unexpected surge in the number of scholars who pivot their work to the prizewinning topic (5), and their ideas diffuse across scientific disciplines more broadly than equally cited, nonprizewinning ideas (14). Prizewinners' protégés are prone to become prizewinners themselves, creating lineages of influence that can span generations (12, 23–27).

While prizewinners are heralded by scientists, governments, and the public, research on prizewinning has called into question prizewinners' influence on science. The 41st chair problem posits that there are typically more equally good contenders for a prize than there are prizes (1), which potentially leads to equally strong ideas not receiving equal attention. Relatedly, as prizes have proliferated over time, they have become more concentrated among fewer prizewinners. This raises concerns that a diminishing fraction of innovative ideas are gaining attention (14), which can potentially limit the breadth of ideas in science (14) and can underrepresent different demographic groups (2, 15, 26, 28–30). Consistent with these concerns, researchers and policy analysts argue that more research is needed to understand leadership in science and the conditions that favor scientific innovation (4, 31–33).

Here, we address questions about whether prizewinning scientists are more innovative than equivalently productive and impactful nonprizewinning contenders. We use science prizes as a measure of a shared community belief that the prizewinner's work is exceptionally innovative (2). Our data include information on over 2,460 prizes that were conferred on 7,353 worldwide prizewinners. In conjunction with the prize dataset, we created two more original datasets. The second dataset comprises up to five matched nonprizewinners who are from the same field and career stage, and who have citation and productivity records that are statistically indistinguishable from the prizewinners' records up to the year of the prize, for a total sample of 23,562 prizewinners and matched nonprizewinners (4,470 prizewinners were successfully matched, with each having an average of 4.27 nonprizewinners). The third dataset measures the embeddedness of the collaboration networks of prizewinners and matched nonprizewinners (34–36).

Significance

Using a sample of thousands of science prizes worldwide, this study compares the career-wide innovativeness of prizewinners and a matched sample of similarly impactful nonprizewinner contenders. Scientific prizewinners are more likely to produce papers that combine existing ideas in new ways, join foundational and current research on a topic, and are more interdisciplinary than their matched nonprizewinning peers. Prizewinners' exceptional innovativeness is associated with unique network embeddedness. Relative to nonprizewinners, prizewinners' collaborations have shorter durations, involve more frequent exposure to new topics, and display less overlap among collaborators.

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Data

We assembled data on 2,460 international scientific prizes and their 7,353 recipients (1900–2018) using data from official prize websites and Wikipedia. Prizewinner data included awards and award dates, research topics studied, and publications that significantly expanded prior prize datasets (5, 14). The data used to compute the innovation measures were curated from OpenAlex (37) via its citation network records (38). OpenAlex employs an advanced author name disambiguation algorithm to identify prizewinners by using their names, publication records, affiliations, citation patterns, and external identifiers like ORCID (*SI Appendix*, section 1 and Tables S1 and S2 report descriptive information on the combined prize/prizewinner dataset).

Innovativeness Measures

To quantify a range of accepted operationalizations of innovativeness used in science, we employed three popular, replicable, and validated measures (39). Our first measure is "novelty." Novelty measures the degree to which a scholar's papers combine prior knowledge in conventional or novel ways (40). Novel papers combine past knowledge in ways that have not been or rarely have been combined before. Conventional papers combine knowledge in familiar ways (36, 41–43). Quantitatively, the more a paper combines the work listed in its bibliography in ways that are less than expected by chance, the more it combines ideas in new or rarely seen-before ways. Conversely, the more a paper combines the work referenced in its bibliography in ways that are greater than expected by chance, the more it combines ideas in familiar, seen-before ways (see *SI Appendix*, section 2.1 for details).

Our second measure is "convergence" (32, 44). Convergence measures the degree to which a paper integrates foundational and recent ideas on a topic (7, 32, 33, 44–47). By linking foundational and recent ideas on a topic, high-convergence papers join a topic's original thinking with new thinking and findings, inventively adapting historical ideas to modern problems or emerging applications (32). To capture the integration of historically foundational ideas and the latest thinking on a topic, we compute convergence as the mean and coefficient of variation (CV) of the publication years of a paper's references with respect to the focal paper's publication year. For each focal paper, we calculate the age differences between the publication year of the focal paper and all of the papers it references and then compute the mean and CV of ages. When the age difference between the focal paper's publication year and its references' publication years has a low mean age but a high CV, the focal paper connects historical and present-day insights into a topic (see *SI Appendix*, section 2.2 for details).

Our third measure of innovativeness is "interdisciplinarity" (36, 48–52). Interdisciplinarity measures the degree to which a scholar's work incorporates disparate subject categories; here, we use the level-1 concept in OpenAlex as the subject categories. We compute a focal paper's interdisciplinarity as $\Delta = \sum_{ij(i \neq j)} d_{ij} p_i p_j$, where p_i and p_j are the proportion of the focal paper's citing papers in subject categories i and j. d_{ij} is the cosine dissimilarity score between i and j, which is calculated through the cocitation matrix for all papers. The value Δ ranges from 0 to 1, and higher values indicate that the paper is more interdisciplinary (see *SI Appendix*, section 2.3 for details).

To ensure that the three measures load on the same underlying construct, we conducted a principal component analysis (PCA). Novelty, convergence, and interdisciplinarity loaded in distinct directions within a broader, multidimensional space. The PCA indicated that these measures capture related but different aspects of innovation (39), which is consistent with the low bivariate correlations between novelty and convergence (0.018), novelty and interdisciplinarity (0.035), and convergence and interdisciplinarity (0.037) (see *SI Appendix*, section 2.4 and Table S3 and Fig. S4 for details).

Matching Procedure

We utilized coarsened exact matching (CEM) (53) and dynamic optimal matching (DOM) (54) methods to construct comparable groups of prizewinners (PWs) and matched nonprizewinners (NPWs) up to the year each PW received their first award. CEM matches PWs and NPWs based on fixed categorical variables. DOM matches PWs and NPWs based on their time-varying attributes on a year-by-year basis. For example, if total citations are spread over five publications a year, DOM looks for matches where the distribution of citations over papers in a single year is equivalent between PWs and NPWs to account for surges in productivity or high-impact publications. The variables selected for matching include these six characteristics: a) discipline, b) first publication year (research age), c) total number of publications before the prizewinning year, d) total number of citations before the prizewinning year, e) yearly number of publications, and f) yearly citations before the prizewinning year.

According to the CEM procedure, we identify for each prizewinner their first publication year, first prizewinning year, research discipline, total number of publications, and the total number of citations to create initial super groups of matched PWs and NPWs (≤ 200 for each PW) where the first year of publication can vary by ± 2 years and total publications and citations can vary by ± 30% relative to the target PW before their prizewinning year. Within each initial super group, we used DOM to further select the NPWs whose dynamic fluctuations in yearly publications and citations were statistically indistinguishable from the PWs. We define the distance measure ($d^p_{i,j}$) for PW i and the NPW j based on the yearly number of publications and yearly number of citations ($d^c_{i,j}$) t_0 years before the prizewinning year, as follows,

$$d^p_{i,j} = \frac{1}{t_0 + 1} \sum_{t=t^*-t_0}^{t^*} \frac{|Y_i(t) - Y_j(t)|}{Y_i(t)},$$

where $Y_i(t)$ presents the number of publications of PW i at year t, t^* represents the prizewinning year of PW i, and we traced back the matching for t_0 years before the prizewinning year. The same definition is used for distance $d^c_{i,j}$ for the number of citations (see *SI Appendix*, section 3.1.1 and Fig. 1*A* for the procedure details). To ensure the closeness and balance between the PWs and NPWs for the entire system, for each PW, we selected up to five matched NPWs from the super-group pool who have the smallest distance within a distance threshold (*SI Appendix*, section 3.1.2 and Figs. S7 and S8 use different thresholds and confirm the robustness of our results). NPWs not meeting the threshold were omitted from the analysis. Fig. 1 *B* and *C* shows that the raw data on the number of papers and the number of citations for the PWs and NPWs with 95% CIs have no statistically significant differences before the prizewinning year.

Numerous tests confirmed the robustness of the matching. First, *SI Appendix*, section 3.1.2 and Figs. S7 and S8 indicate that the results are robust to different thresholds. Second, Mahalanobis distance tests (55–57) in the DOM procedure demonstrated that results are robust to different distance methods (see *SI Appendix*, section 3.2.2 and 4.5.1 and Fig. S10 and Table S8; *SI Appendix*,

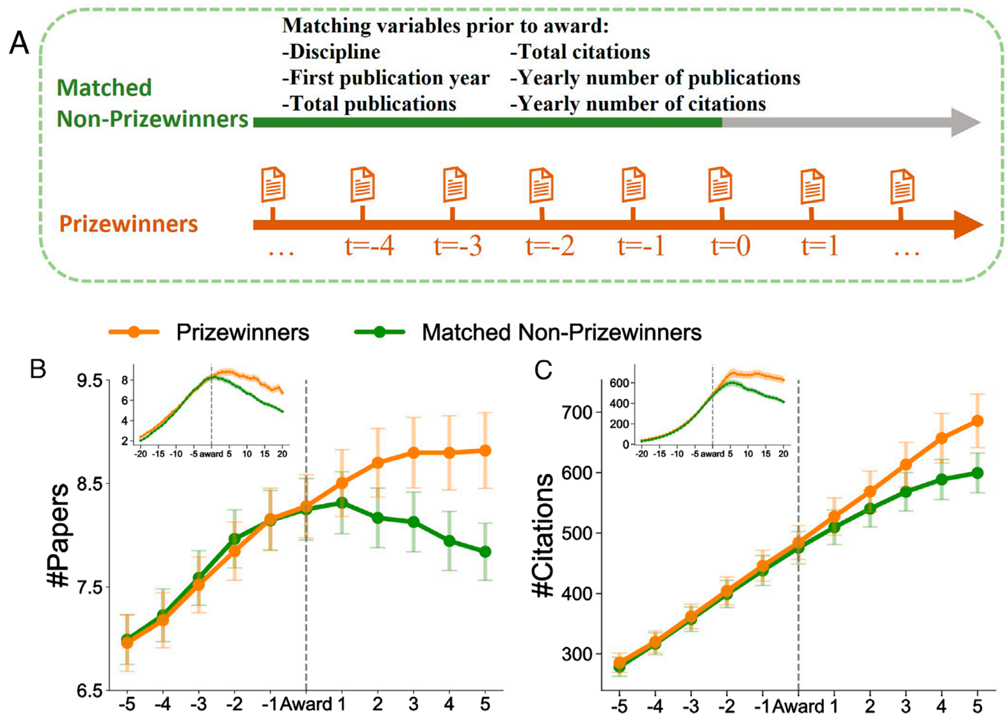

Fig. 1. Matching Process and Validation. (*A*) Procedures for matching prizewinners with up to five nonprizewinners who have statistically indistinguishable impact and productivity records with the prizewinning scientists before the prizewinning year using CEM and DOM techniques. (*B* and *C*) confirm matching for productivity (# papers) and productivity (# citations) with 95% CIs. Insets show data for 20 y before and after the prize year. t = 0 is the prizewinning year.

section 3.2.3 and Table S4, t tests all P-values > 0.5 and all SMD tests < 0.1). Third, the above results are robust to adding team size, which is defined as the number of coauthors per paper (*SI Appendix*, section 3.2.1 and Fig. S9), and dynamically matching the three innovativeness variables (*SI Appendix*, section 3.2.4 and Fig. S11).

Innovation Gap

Fig. 2 (*A*-*C*) reports the raw data values of papers for PWs and NPWs for each innovativeness measure. The x-axes show career time. The prizewinning year is designated as t^* on the x-axis, and the y-axes show the percentage of innovative papers written by PWs, NPWs, and a random sample of scholars (for each prizewinner, we randomly select five nonprizewinning scholars in the same discipline, 22,350 random scholars in total) on three separate plots for A) novelty, B) convergence, and C) interdisciplinarity with 95% CIs. Figure insets show the same relationships when the innovation variables are included in the dynamic matching to ensure that the inclusion or exclusion of these variables do not alter the results.

The plots reveal several notable observations about the innovativeness of different classes of scholars over a career. First, for all three outcome variables, PWs' and NPWs' curves run parallel to each other. This pattern indicates that while PWs and NPWs differ in their levels of innovativeness, their trends in innovativeness mirror one another, in that they broadly move at the same time and in the same direction. For example, when PWs' innovativeness rises or falls, NPWs broadly parallel those changes, except for the period just prior to the prize year when the innovativeness of PWs begins to exceed that of NPWs. By contrast, a random sample of scholars follows a different pattern of innovativeness relative to PWs and NPWs, and their level of innovativeness is always significantly below that of PWs and NPWs.

Second, while PWs' and NPWs' growth and decline trends in innovativeness within any particular form of innovation mirror each other, the trends differ across innovation measures. Novelty (Fig. 2*A*) continually increases over a career. By contrast, convergence and interdisciplinarity (Fig. 2 *B* and *C*) appear relatively flat during a scholar's early to midcareer stage and then continue to decline over the remainder of a career.

Third, just prior to the prize year, the innovativeness of PWs and NPWs begin to diverge. About four to five years before the prize, PWs' innovativeness begins to exceed that of NPWs and gradually and continually widens up until the prize year, at which point the difference in innovativeness peaks. After the prize year, the innovation gap between PWs and NPWs stabilizes at roughly the peak level and then persists until the end of their careers. This result suggests that on average, scholars' innovativeness precedes their prizewinning and that prizewinners' relatively high innovativeness persists over the remainder of their careers. Relatedly, it is noteworthy that when a PWs' greater level of innovativeness emerges before the prize year, it occurs when PWs' and NPWs' productivity and impact are statistically indistinguishable (Fig. 1). This result indicates that PWs initially diverge in innovativeness not by increasing their productivity or citation rates relative to NPWs but by publishing more innovative work at levels of productivity and impact comparable to matched NPWs. Thus, PWs innovativeness increases on a paper-by-paper basis prior to the prize. Fig. 2 insets show the same analysis when the innovation variables are added to the matching process, which guarantees equivalence in innovation before the prize. The insets show that PWs diverge from NPWs in terms of the innovativeness of their papers, a gap that widens up to the prize year and persists at roughly the peak level thereafter.

To more precisely quantify the estimated differences between PWs and NPWs, we separately regressed each innovation variable on an indicator variable for prizewinning (1 = Yes), an interaction term for *prizewinner* × *post*, and controls variables including team

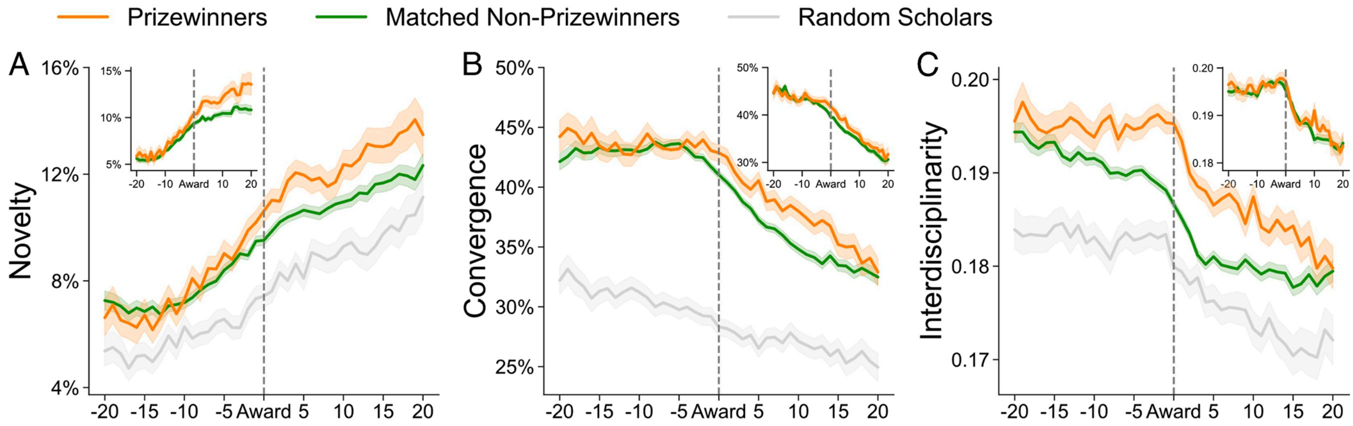

Fig. 2. Observed Innovativeness of Prizewinners, Matched Nonprizewinners, and a Random Sample Group. The y-axis shows the (*A*) percentage of novel papers, (*B*) percentage of convergence papers, and (*C*) mean interdisciplinarity values for prizewinners (PWs), nonprizewinners (NPWs), and a random sample of authors with 95% CI. The prizewinning year is designated on the x-axis as zero. The values of innovativeness for PWs and NPWs mirror one another over their careers and show no statistical differences in innovativeness about four to five years before the prize when PWs' and NPWs' innovativeness diverges and grows, peaks at the prize year, and then persists on all three measures of innovativeness over the remainder of their careers. Insets show the same relationships when the innovation variables are dynamically matched in the DOM procedure.

size, matched group, prize, publication year, and author position. This regression resembles a difference-in-difference regression (39) and is used here to estimate statistical rather than causal relationships and to confirm the parallel trends requirement of PWs and NPWs before prizewinning (shown in *SI Appendix*, section 4.2) (58). We avoid making causal inferences because the proxy "treatment" variable, namely prizewinning, is not random but partially predictable through media coverage, informal conversations, or bibliographic data (27, 59).

In Fig. 3, Panel A reports the regression results comparing PWs' and NPWs' innovativeness. Consistent with the raw data findings, the regression variable *Prizewinner* confirms that PWs display higher levels of research innovation than NPWs in terms of novelty, convergence, and interdisciplinarity ($P < 0.05$, $P < 0.01$, and $P < 0.001$, respectively). The interaction term *Prizewinner* × *post* indicates that PWs relative to NPWs display significantly wider gap in their research novelty and convergence after the prize year ($P < 0.001$ for both variables). By contrast, the insignificant interaction of *Prizewinner* × *post* for interdisciplinarity indicates that PWs produce more interdisciplinary research than NPWs, but the innovation gap for interdisciplinarity before and after the prize does not differ in magnitude. Fig. 3, Panel B, presents margin plots based on the regression models. We observe that PWs and NPWs display overlapping levels of innovativeness during their formative career years, with PWs showing a gradually widening, significant research innovation gap over NPWs that first emerges roughly in the five years before the prize year, peaks at the prize year, and then persists at that level after the prize year.

The SI presents several robustness checks. First, *SI Appendix*, Table S5 reports a robustness check for separate disciplines; *SI Appendix*, Fig. S13 reports a robustness check when the sample is split into high and nonhigh prestigious prizes; and *SI Appendix*, Table S6 reports robustness checks when the data are split into the periods of before and after 1990 or of just the last 30 y of data (*SI Appendix*, section 2.4 and Fig. S5 *A–I*). Second, we conduct goodness of fit replication regression analysis using nonlinear random-forest models (*SI Appendix*, section 4.5.5), *SI Appendix*, Fig. S15 reports actual vs predicted value plots, and staggered DID models are presented in *SI Appendix*, section 4.5.4 and Table S11). Additional specifications that control for PWs who win multiple prizes (*SI Appendix*, section 4.5.2 and Table S9) and include or omit review papers confirmed the main results (see *SI Appendix*, section 4.5.3, and Table S10 for details).

Embeddedness and Innovation

Prizewinners' collaboration networks and innovativeness may be interrelated. The embeddedness of a researcher's network has been found to be positively associated with innovation through access to information, trust-building, and a decrease in process losses. (36, 60–63). Networks have also been found to be negatively related to innovation in that they can become echo chambers of like-mindedness (35, 60, 62, 64, 65). To examine embeddedness' potential role in the innovativeness of PWs and NPWs, we operationalized the embeddedness of PWs', NPWs', and the random sample of scholars' coauthorship networks using three embeddedness measures: tie duration, tie overlap, and topic similarity (35, 60, 66–69). Tie duration quantifies the average length of a coauthorship relationship. If a scholar collaborates on a paper that was published in 1995 with two coauthors (e.g., A and B), and the scholar's first collaboration record with A was in 1990, and with B was in 1991, then the duration of the ties associated with the 1995 paper is 4.5 y (9 total years divided by the two coauthors) (*SI Appendix*, section 5.1 and Fig. S16*A*). Tie overlap uses the Jaccard index to measure the size of the intersection of coauthors divided by the size of their union (J). If, before publishing a joint paper with coauthors A and B, coauthor A had six total collaborators and B had eight, of which three overlapped, then $J = 3 \div 11 \approx 0.273$ (see *SI Appendix*, section 5.1 and Fig. S16*B*). Topic similarity quantifies the similarity between a scholar's prior research topics and the topic(s) of the focal paper. For instance, if a scholar has published papers covering 12 distinct topics prior to the focal paper, and the focal paper encompasses four topics, of which two appeared in prizewinner's prior research topics, the topic similarity value for the focal paper would be 0.17 (=2/12) (*SI Appendix*, section 5.1 and Fig. S16*C*). We used the fine-scale concepts classifications in OpenAlex to identify distinct topics.

Fig. 4 presents the raw data for our embeddedness variables for PWs, NPWs, and the random sample of authors. The x-axes and y-axes represent career time and levels of tie duration, tie overlap, and topic similarity (95% CI shown), respectively. Over time, PWs', NPWs', and random authors have levels of embeddedness that move in parallel. PWs on average have lower levels of embeddedness than NPWs, and NPWs have lower levels of embeddedness than random authors on all measures. Further, topic similarity and tie overlap are positively correlated with each other and negatively correlated with tie duration, suggesting the main difference

A

	Model 1	Model 2	Model 3
	Novelty	Convergence	Interdisciplinarity
Prizewinner	0.003* (0.002)	0.009** (0.003)	0.004*** (0.001)
Prizewinner×post	0.012*** (0.002)	0.012*** (0.003)	0.001 (0.001)
Novelty	--	<-0.001 (0.001)	0.014*** (0.000)
Convergence	<-0.001 (0.000)	--	0.002*** (0.000)
Interdisciplinarity	0.217*** (0.005)	0.067*** (0.008)	--
Prize	Y	Y	Y
Team size	Y	Y	Y
Matched group	Y	Y	Y
Author position	Y	Y	Y
Publication year	Y	Y	Y
Constant	0.055*** (0.001)	0.386*** (0.002)	0.184*** (0.000)
Observations	2,838,611	2,838,611	2,838,611
R-squared	0.037	0.065	0.140

Robust standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05.

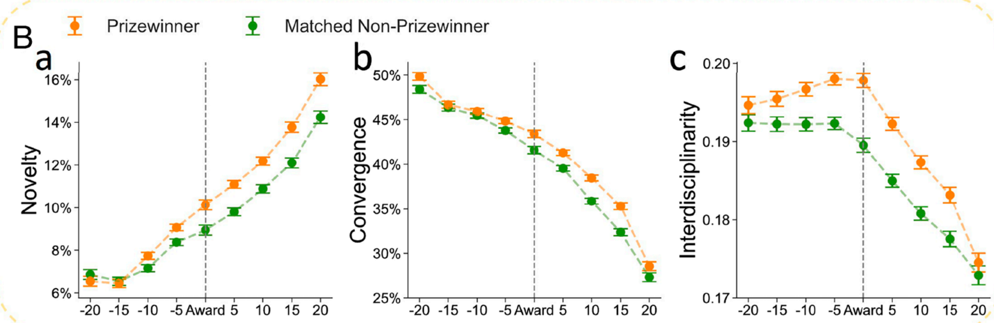

Fig. 3. Regression Estimates of Prizewinners' and Matched Nonprizewinners' Innovativeness. (*A*) Each model controls for the fixed effects of PWs and NPWs matched groups, team size (six categories, 1, 2, 3, 4, 5, >5), prize, publication year (relative to the prizewinning year), and author position (see *SI Appendix*, section 4.3 for the model specifications). (*B*) Figures a–c represent the model-estimated innovativeness by career years (95% CIs). The estimated growth and decline patterns of PWs and NPWs mirror one another over their careers except for interdisciplinary. At the boundary of roughly five years before the prize, PWs gradually grow more innovative than NPWs, a gap that peaks at the prize year and continues for the remainder of their careers (see *SI Appendix*, section 4.4 for the model specifications).

in the embeddedness of PWs and NPWs networks is more a matter of magnitude than structural form.

Table 1 regresses our three innovativeness variables on the network embeddedness of PWs and NPWs. The regressions control for whether the focal scholar is a PW (1 = Yes), pre- and postprize periods (1 = Yes), and fixed effects for prize, team size, publication year, matched group, and author position (*SI Appendix*, section. 5.2 for model specifications). The regressions reveal several links between embeddedness, prizewinning, and innovation. First, for both PWs and NPWs, network embeddedness predicts innovativeness. In eight out of nine coefficients, tie duration, tie overlap, and tie similarity are all highly significant and inversely associated with a scholar's novelty, convergence, and interdisciplinarity. Second, the significant relationships between embeddedness and innovation when all embeddedness variables are simultaneously controlled in the model indicate that their relationships with innovation are additive. For example, the lower the tie duration, tie overlap, and topic similarity, the greater a PW or NPW's innovation. Third, after accounting for collaboration network patterns, the coefficients for *Prizewinner* are still positive and significant. These results suggest that prizewinning is not fully accounted for by a scholar's network of collaboration. To test whether these differences in relative innovativeness are due to PWs' coauthors being more productive and cited than those of NPWs, we explored the productivity and citation impact of the coauthors of PWs and NPWs in our data and found no differences. *SI Appendix*, Fig. S17 shows that over careers, the productivity and impact of the coauthors of PWs and NPWs are equivalent.

Discussion

Prizewinners disproportionately influence science. With prizes proliferating worldwide and the effectiveness of science's traditional reward systems being debated, a key question is how prizewinners' innovativeness compares with that of less celebrated scientists. We quantify and compare the innovativeness of 23,562 prizewinners (PWs) and matched nonprizewinners (NPWs) who had statistically indistinguishable impact and productivity records before the prize year. Our results showed that PWs are significantly more innovative than NPWs. Prizewinners are more likely to combine existing knowledge in novel ways, connect foundational and cutting-edge ideas on a topic, and draw on interdisciplinary perspectives. Also, we found that a distinguishing predictor of the prizewinners' greater innovativeness is their embeddedness in collaborative relationships. In contrast to matched nonprizewinners, prizewinners have shorter-term collaborations, engage more often with research areas that are new to them, and have less overlap with their collaborators' collaborators. Dynamically, assuming no differences in productivity and impact prior to the prize, PWs' innovativeness begins to diverge significantly from NPWs at about 5 y before the prize, then widens consistently until the prize year, when the gap peaks and thereafter stabilizes at roughly the peak level over the remainder PWs' careers.

The implications of our analysis for reward systems are associated with the Matthew Effect, a concept that holds that in practice prizewinners receive more rewards and recognition—fame, funds, or collaborators—than their peers, regardless of the actual quality of their current work (1). Aiming to extend prior research on

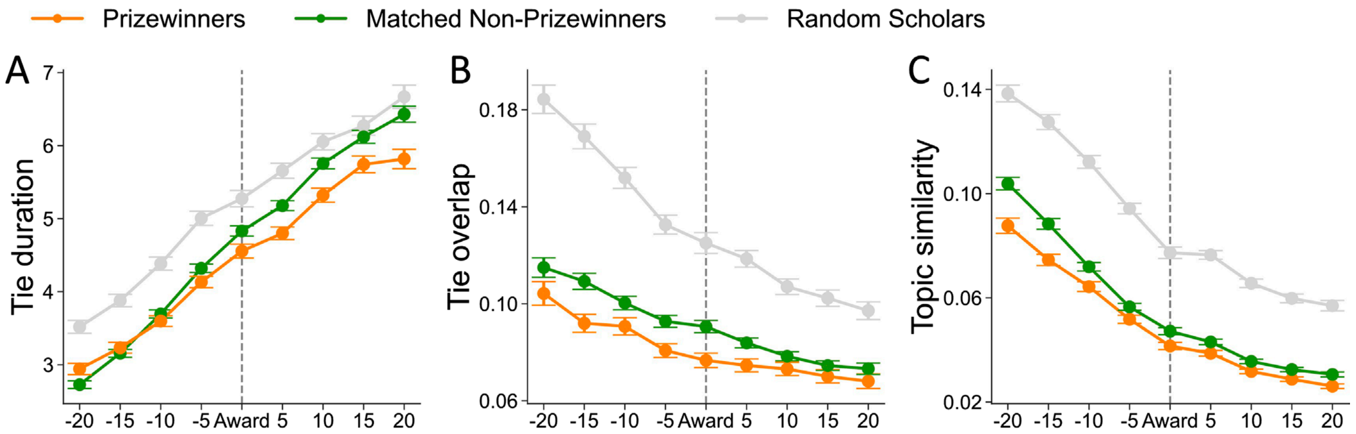

Fig. 4. Network Embeddedness Dynamics. The dynamics of tie duration (*A*), tie overlap (*B*), and topic similarity (*C*) over the scholars' careers. Dots denote the averages, and error bars represent the 95% CI. Orange lines are for PWs, green lines are for NPWs, and gray lines are for random scholars.

scientific rewards systems, our work examined both preprize and postprize Matthew Effects. In contrast to prior research, our analysis uses a large sample of diverse prizes worldwide, rather than a single prize. Further, we created a five-to-one sample of dynamically matched nonprizewinners who had the same career age, worked in the same discipline, and had statistically indistinguishable records of productivity and impact with each prizewinner.

The implications of our investigations relate to thinking on Matthew Effects, prizewinners, and prizes in two primary ways. First, our preprize results demonstrate that although prizewinners and matched nonprizewinners have no statistical differences in their productivity or impact up to the prize year, in 4 to 5 y before the prize, prizewinners grow increasingly more innovative than matched nonprizewinners. They publish significantly more work that combines existing research in new ways, integrates historical and contemporary ideas on a topic, and is more interdisciplinary. This result suggests that among equally outstanding researchers, greater innovation in research is significantly associated with prizewinning.

Second, to examine postprize Matthew Effects, we tested whether prizewinners experience cumulative advantages relative to nonprizewinners after receiving their prize. To examine this relationship, we split our prize data into high and low prestige prizes under the assumption that high prestige prizes confer greater recognition on a prizewinner than low prestige prizes. The results appear unsupportive of the Matthew Effect. On average, for our over 2,000 prizes, we found that a prize's prestige does not predict cumulative advantage. The prizewinners of both high and low prestige prizewinners have similarly sized innovation gaps relative to nonprizewinners when the prize is conferred. Further, we found that the size of the innovation gap does not grow after the prize: The stability of the innovation gap suggests that prizewinning is not associated with the acquisition of undue resources after winning a prize. Finally, inconsistent with Matthew Effect expectations that winning a prize would result in prizewinners acquiring

Table 1. Prizewinner's network embeddedness and innovation

	Model 1	Model 2	Model 3
	Novelty	Convergence	Interdisciplinarity
Prizewinner	0.005* (0.002)	0.008* (0.004)	0.006*** (0.001)
Prizewinner × post	0.013*** (0.003)	0.012** (0.004)	<−0.001 (0.001)
Tie duration	−0.001*** (0.000)	−0.015*** (0.000)	−0.001*** (0.000)
Tie overlap	−0.018*** (0.003)	−0.014** (0.005)	−0.026*** (0.001)
Topic similarity	−0.034** (0.011)	−0.016 (0.020)	−0.250*** (0.005)
Novelty	–	−0.001(0.002)	0.013*** (0.000)
Convergence	<−0.001 (0.001)	–	0.002*** (0.000)
Interdisciplinarity	0.239***(0.006)	0.075*** (0.010)	–
Prize	Y	Y	Y
Team size	Y	Y	Y
Matched group	Y	Y	Y
Author position	Y	Y	Y
Publication year	Y	Y	Y
Constant	0.071*** (0.001)	0.489*** (0.002)	0.194*** (0.000)
Observations	1,750,607	1,750,607	1,750,607
R-squared	0.039	0.069	0.167

Each model controls for the fixed effects of PWs and NPWs matched groups, team size (six categories, 1, 2, 3, 4, 5, >5), prize, publication year (relative to the prizewinning year), and author position (see *SI Appendix*, section 5.2 for model specifications). First, tie duration, tie overlap, and topic similarity are significantly and inversely related to novelty, convergence, and interdisciplinarity, except for one case, convergence and topic similarity. After accounting for a scholar's embeddedness, prizewinners are still more innovative than matched nonprizewinners, suggesting that individual characteristics of scholars and their embeddedness in collaboration networks are associated with the level of innovativeness.Robust SE in parentheses, ****P* < 0.001, ***P* < 0.01, **P* < 0.05.

more distinguished coauthors after the prize, we found that prizewinners do not work with coauthors who have greater productivity and impact than the coauthors of nonprizewinners before or after the prize.

There may be several reasons why our findings do not cohere with some expectations of the Matthew Effect. First, it is conceivable that after being awarded a prize, a scholar may hone or have acquired the skills needed to communicate innovative ideas (70), making them more likely to publish more innovative work in the future independently of any increase in their status. Second, if a prizewinner establishes a new or innovative topic space, the new topic space may give the prizewinner first mover advantages that may include early access to opportunities to shape the topic's direction, attract collaborators, and set foundational precedents even if their level of renown has not changed (71). Third, since 1968 when Robert Merton first suggested that the Matthew Effect was operating in science, it may be that science's self-correcting mechanisms have made prize committees vigilant of avoiding the disadvantages of Matthew Effects on scientific reward systems (72).

These results also shed light on the debate about rates of innovation in science. After a study using the disruption index (33) reported that scientific innovation is declining, policy analysts and scholars have debated the results (73, 74) and called for more theoretical and empirical research on innovation. In contrast to methods that use the disruption index, which purportedly measures scientific innovation by the publication rate of papers with revolutionary ideas that topple conventional thought, the multiple measures we used view innovation as a process by which past knowledge is recombined to form original or rarely seen ideas. Our findings indicate that different measures of innovation capture different facets and imply different inferences about scientific innovation, suggesting that innovation is a multifaceted construct that requires examination by a range of conceptual and philosophical foundations (75). Thus, even if there is the decline in single paper disruptiveness is eventually validated, other possible paths to innovation in science may coexist. For example, incremental but novel papers could result in multiple lines of evidence that together can divide and conquer a larger problem that historically was addressed in a single breakthrough paper. For example, plate tectonics theory synthesized different contributions that tackled separate pieces of the broader puzzle—continental shift, oceanic structure, magnetic patterns, and earthquake dynamics. Along these lines, if scientists are increasingly equipped to solve a specialized part of a larger puzzle (25) and solve big problems through a divide-and-conquer strategy, then future research should examine how new and emerging social and AI technologies facilitate scientists' abilities to combine attention, expertise, and ideas.

Finally, while this study examined reward systems from the lens of the Matthew Effect and finds evidence supporting the conclusion that prizewinners are more innovative than matched nonprizewinners, achieving equality and eliminating biases in reward systems is an ongoing challenge for future research. Indeed, the tension between the ideal of merit-based scientific recognition and the reality of inequality in prizes goes beyond Matthew Effects and continues to require sustained research. For example, while prizes and innovativeness may be statistically related, other bias can exist in the system in terms of access to education, labs, funding, leadership, and demographic-based roles, or the forms of innovation that are chosen to be rewarded. Future studies should continue to improve how scientific contributions are equitably recognized, remove existing bias from scientific reward systems, and endeavor to design systems that fairly reward scientists and promote advancement in science and society.

Data, Materials, and Software Availability. Data and code for reproducing the main results data have been deposited in GitHub (https://github.com/ChaolinTian/innovative-distinctions-of-prizewinners-and-their-networks) (38).

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