Decoding team and individual impact in science and invention

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Scientists and inventors increasingly work in teams, raising fundamental questions about the nature of team production and making individual assessment increasingly difficult. Here we present a method for describing individual and team citation impact that both is computationally feasible and can be applied in standard, wide-scale databases. We track individuals across collaboration networks to define an individual citation index and examine outcomes when each individual works alone or in teams. Studying 24 million research articles and 3.9 million US patents, we find a substantial impact advantage of teamwork over solo work. However, this advantage declines as differences between the team members' individual citation indices grow. Team impact is predicted more by the lower-citation rather than the higher-citation team members, typically centering near the harmonic average of the individual citation indices. Consistent with this finding, teams tend to assemble among individuals with similar citation impact in all fields of science and patenting. In assessing individuals, our index, which accounts for each coauthor, is shown to have substantial advantages over existing measures. First, it more accurately predicts out-of-sample paper and patent outcomes. Second, it more accurately characterizes which scholars are elected to the National Academy of Sciences. Overall, the methodology uncovers universal regularities that inform team organization while also providing a tool for individual evaluation in the team production era.

team science | collaboration | prediction | team organization

Teams are increasingly prevalent across virtually all fields of science and patenting (1–4), raising fundamental questions about the nature of team-based creativity and team assembly and creating fundamental challenges for individual assessment (5–11). For example, while Heisenberg developed his uncertainty principle without building a team and received credit in a straightforward manner as the solo author, more recent breakthroughs, such as Milstein and Kohler's monoclonal antibodies and Faggin, Hoff, and Mazor's microprocessor, often come from collaborations that both combine and obscure individual contributions (2, 4, 5). Here we investigate two intertwined questions. First, how do individuals combine to predict team output? Second, how can individual impact be inferred when people work in teams?

Concretely, consider a paper written by two individuals. At one extreme, the team outcome could be a max process, $y = max\{a_{low}, a_{high}\}$, where y is the success of the joint outcome, a_i is an index characterizing each individual team member, and $a_{high} \geq a_{low}$. In this max specification, the joint output is determined by the higher-index individual; for example, perhaps this individual, by shaping the research question and methods, drives the ultimate success of the project. By contrast, at the other extreme, team outcomes could be a min process, $y = min\{a_{low}, a_{high}\}$, where the joint result is determined by the lower-index individual. For example, perhaps this team member creates bottlenecks at certain tasks and determines the ultimate outcome. Alternatively, the outcome may lie between these max and min extremes, perhaps as the arithmetic, geometric, or other mean of the individual indices.

These alternative views have fundamentally different—indeed, opposite—implications for science. Organizationally, in a max specification, a team could expect a successful outcome so long as one person has a high index, and an organization might sprinkle around its best people to great effect (12–14). However, in a min specification, the opposite is true. Here the person with the lowest index on a team would determine the outcome, and the collective output of science would be greatest not by sprinkling the top people around but rather through positive assortative matching, where individuals of similar index measures work together (14–16). Credit considerations in collaboration (5, 10, 17, 18) are also germane; in a max specification, audiences would reward the top author, akin to some versions of the Matthew effect (5), but in a min specification the joint outcome is informative for the lowest-index member of the team (17). Of course, the true relationship may lie between these max and min extremes.

This paper introduces a transparent and computationally feasible method for informing the relationship between individual and team outcomes. This descriptive approach is applied both to reveal central facts about science and invention and to predict individual and team results. We leverage the generalized mean (or Hölder mean) to write

$$y = \beta_n \left[\frac{1}{n} \sum_{i=1}^{n} a_i^{\rho} \right]^{\frac{1}{\rho}}, \qquad [1]$$

where y is the outcome and n is the team size. The parameters a_i track individuals across their works to estimate a fixed effect for

Significance

Scientists and inventors increasingly work in teams. We track millions of individuals across their collaboration networks to help inform fundamental features of team science and invention and help solve the challenge of assessing individuals in the team production era. We find that in all fields of science and patenting, team impact is weighted toward the lower-impact rather than higher-impact team members, with implications for the output of specific teams and team assembly. In assessing individuals, our index substantially outperforms existing measures, including the h index, when predicting paper and patent outcomes or when characterizing eminent careers. The findings provide guidance to research institutions, science funders, and scientists themselves in predicting team output, forming teams, and evaluating individual impact.

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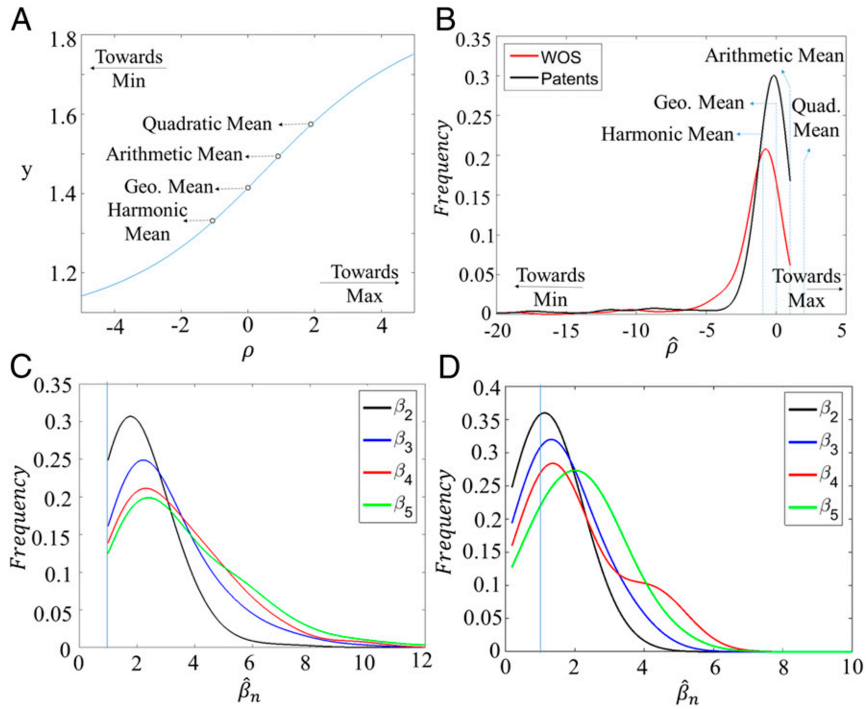

Fig. 1. The generalized mean. (*A*) An example of the generalized mean function for two individuals. (*B*) The distribution of the generalized mean parameter $\hat{\rho}$ across Web of Science fields (red) and patenting fields (black). (*C*) The distributions of the team impact parameters ($\hat{\beta}_2, \ldots, \hat{\beta}_5$) across Web of Science fields. (*D*) The distributions of the team impact parameters ($\hat{\beta}_2, \ldots, \hat{\beta}_5$) across patenting fields.

individual i on a per-paper (or per-patent) basis. The key team parameter is ρ, which defines how the individual parameters a_i combine. At the extremes, the Hölder mean allows for the max ($\rho \to \infty$) and min ($\rho \to -\infty$) functions while also incorporating other means, including the arithmetic mean ($\rho = 1$), geometric mean ($\rho = 0$), and harmonic mean ($\rho = -1$) as special cases (Fig. 1*A*). An important intuition is that the person with the lowest (highest) a_i becomes more influential for the joint output as ρ declines (increases). The arithmetic mean provides the boundary where each individual is equally important.

In addition, the parameter β_n captures impact benefits associated with teamwork (specifically, for a team of size n), including advantages of aggregating effort, skill, or marketing, as well as disadvantages through coordination costs in teams (1, 2, 4). We normalize the model by setting $\beta_1 = 1$ for solo-authored work. This normalization implies that $y = a_i$ for solo-authored work. Thus, the individual index (the estimated a_i) is interpreted as the expected outcome when that person works alone. Further, taking a team of size n, the magnitude of $\hat{\beta}_n$ is interpreted as the outcome advantage of teamwork over solo-work when the individual team members share a common value of a_i.

We estimate this function, by field, in two large datasets. First, for research articles, we examine all 182 different fields of science, engineering, social sciences, and arts and humanities in the WOS that have at least 500 papers in the field. Second, for patents, we examine all 384 different primary technology classes of the US Patent and Trademark Office (USPTO) that have at least 500 patents in the class. The estimates further deploy name disambiguation to identify a given individual across a body of their work. For the WOS, we use Thomson Reuters' name-disambiguated author dataset (19–21). For the USPTO data, we use Li et al.'s (22, 23) name-disambiguated inventor dataset. We further restrict the data to the 97% of papers and 99% of patents with team sizes of eight or fewer members (24). The team outcome measure in our main analyses is the number of citations received by the paper or patent in the first 8 y after publication (1). We consider robustness to alternative outcome measures in the *SI Appendix*, which also provides further details about these datasets. Our final estimation samples include 24 million research articles written by 13 million individuals (WOS, 1945–2005 period) and 3.9 million patents produced by 2.6 million individuals (USPTO, 1975–2006 period).

Results

Fig. 1*B* presents the distribution of the estimated $\hat{\rho}$ across fields. We see substantial similarity in the science and patenting domains. First, in all fields of science and patenting, we find $\hat{\rho} < 1$. This finding indicates that while everyone on the team has influence, team output is weighted toward the lower-index rather than the higher-index members of the team. This finding is robust to various computational checks (*SI Appendix*) and consistent with raw data analysis as we will show below. The generality of this finding—appearing across diverse fields of sciences, engineering, social sciences, and disparate technology areas of invention, many of which feature different norms and institutions—indicates a profound regularity to team-based research outcomes. Second, we see that the modal field in both the science and patenting domains centers below the geometric average, with median values near the harmonic average ($\hat{\rho}_{median} = -1.49$ for paper fields and $\hat{\rho}_{median} = -0.95$ for patent fields). Third, the distribution is asymmetric toward lower $\hat{\rho}$, with a substantial mass of fields below the harmonic average and a long left tail stretching toward the min specification.

Fig. 1*C* presents the distributions of $\hat{\beta}_2$ through $\hat{\beta}_5$ across fields for the Web of Science (WOS), and Fig. 1*D* presents these distributions for patents. Consistent with literature showing an impact advantage of teams over solo authors in raw data (1, 2, 25), we find that these team-impact parameters are large on average. Focusing on two-person teams, we see that $\hat{\beta}_2 > 1$ for 99% of WOS fields and for 94% of patenting fields. The median

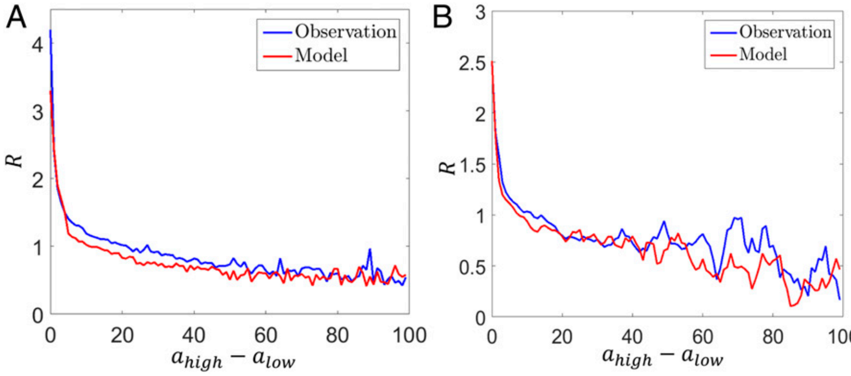

Fig. 2. Team impact. We examine different pairings of individuals in two-person teams. (*A*) The raw data (blue) and the model prediction (red) for the Web of Science. (*B*) The raw data (blue) and the model prediction (red) for US patents. The *x* axis is the difference in individual citation impact, $a_{high} - a_{low}$, between the two authors. The *y* axis is the normalized team outcome, measured as the ratio of the team citation outcome to the arithmetic mean of the team members' individual citation outcomes (see text). We see that the team impact advantage is large when the team members have similar individual impact measures but declines as the difference in individual impact widens within the team.

value is $\hat{\beta}_2 = 2.05$ for papers and $\hat{\beta}_2 = 1.44$ for patents, which rises further for larger teams, with some evidence that the teamwork advantage flattens for team sizes above 4. Notably, these findings indicate a team impact advantage, even when controlling for individual citation impact measures. Thus, the team advantage seen in prior literature (1, 2, 25) is not simply about higher-citation people tending to work in teams but rather appears conditional on the citation impact of the individual team members (10). *SI Appendix*, Tables S1 and S2, provides the estimated $\hat{\rho}$ and $\hat{\beta}_2$ through $\hat{\beta}_5$ for each field of science and patenting.

We thus see two offsetting features in team outcomes. There tends to be an impact advantage of teamwork over solo work ($\hat{\beta}_n > 1$), but this advantage declines as the gap between the team members' individual citation indices grows ($\hat{\rho} < 1$). On net, because the $\hat{\beta}_n$ values tend to be substantially greater than 1, teamwork tends to predict higher impact so long as the gap between the individuals is not itself substantial. Thus, individuals with different citation indices can still see higher impact when working together than working alone. We further find a negative relationship between a field's $\hat{\rho}$ and $\hat{\beta}_2$ (*SI Appendix*, Table S6 and Figs. S1 and S2). This relationship is consistent with a division of labor interpretation (4, 7, 25) where specialization may create substantial teamwork advantages (higher $\hat{\beta}_2$) but also accentuate bottlenecks in production (lower $\hat{\rho}$).

To develop further intuition for these findings and visually examine the fit of the model, we consider different pairings of individuals in two-person teams. We examine the ratio

$$R = \frac{y}{\frac{1}{2}\left(a_{low} + a_{high}\right)}, \qquad [2]$$

where y is the team-based outcome for two individuals and a_{low} and a_{high} are their individual citation indices. Conceptually, $R = 1$ occurs when the team-based outcome is equivalent to the simple arithmetic average of the individual indices, while R will be greater (lower) than 1 if the team-based outcome outperforms (underperforms) the arithmetic average of the individual citation indices.

We first examine raw data, presenting a model-free analog of R. Here we measure y as the observed citation impact of the dual-authored paper and measure each a_i using each individual's solo-authored work and taking the arithmetic mean citation impact of that work. For the modeled version of R, we instead take

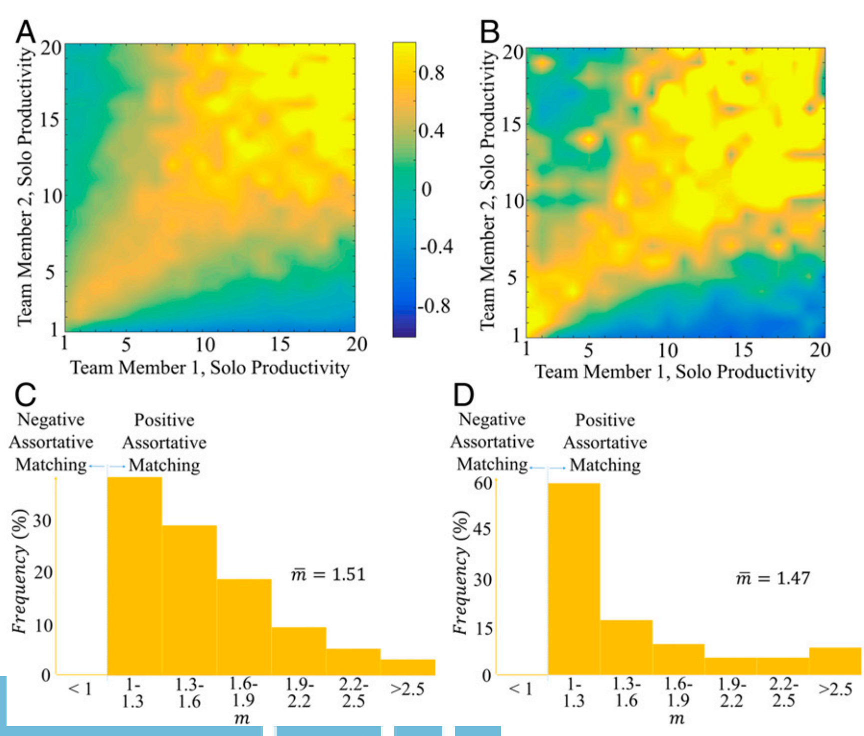

Fig. 3. Team assembly. The tendency for positive assortative matching on individual citation impact for (*A*) dual-authored papers and (*B*) dual-inventor patents. Matching tendencies between individuals are presented according to their solo outcomes, calculated based on each team member's solo works. For each given pairing of individuals, the plotted values are the amount by which the ratio of the observed matching frequency to the frequency expected by chance exceeds 1. The distribution of the mean trace (m) in the collaboration matrix when each field is analyzed separately for (*C*) papers and (*D*) patents. Consistent with $\hat{\rho} < 1$, we see a tendency toward positive assortative matching, which holds across all fields in both domains.

$y = \hat{\beta}_2 \left[\frac{1}{2}(\hat{a}_{low}^{\hat{\rho}} + \hat{a}_{high}^{\hat{\rho}})\right]^{1/\hat{\rho}}$, where $\hat{\rho}$ and $\hat{\beta}_2$ are the model estimates for the relevant field and $\hat{a}_{low}$ and $\hat{a}_{high}$ are these individuals' model-estimated indices using all our data.

Fig. 2*A* shows raw data (blue line) and the model prediction (red line) for the WOS. Fig. 2*B* provides the same comparison for patents. In the figures, the vertical axis presents the moving average of R across all papers or patents with a given difference between the individual team members, $a_{high} - a_{low}$. We see that the model fits the raw data well. This visualization also reveals key intuition and implications. Namely, teams can have a large advantage over solo work, yet differences in individual impact indices within the team reduce this team advantage. Consider Fig. 2 *A* or *B* where the team members have the same index measure ($a_{high} = a_{low}$). Here the dual-authored output has a citation advantage substantially greater than what these individuals achieve alone. The raw data analog here corresponds directly to the model's estimate of β_2. However, as the gap between the individual impact indices widens, the impact advantage of dual-authored papers declines. This decline is consistent with $\rho < 1$, so that the lower index team member dominates in determining the outcome. Had the team outcome been dominated by the higher index team member, then the raw data would slope upward in the figure (which would be consistent with $\rho > 1$). Instead, as we see visually, heterogeneity in individual citation indices is impact-reducing. In fact, although the team advantage is sustained over fairly substantial differences in individual indices, once the differences in individual indices are large enough, teamwork is no longer more impactful as the organizational form. Overall, we see that the estimated team model (1) fits the shape of the raw data closely and that the impact advantages associated with teamwork are dissipated as the citation impact differences between team members grow.

Our next and related results consider team assembly. An organizational implication of $\rho < 1$ is that heterogeneity of individual impact indices tends to reduce joint impact. From this perspective, research organizations would want to match people with similar indices (i.e., positive assortative matching) to maximize total research impact (15, 26, 27). Such sorting has implications for team assembly by individuals and institutions, with potentially wide implications across science and invention given the generality of $\rho < 1$ (12, 28). Our next analyses therefore examine whether teams do indeed assemble to match on individual indices, consistent with our estimates of ρ.

Fig. 3 *A* and *B* focus on two-person teams. As for the raw data analysis in Fig. 2, we measure an individual's impact purely using their solo-authored work, producing an individual-level estimate that is independent of their coauthors. We then ask who works with whom. We present the ratio of (i) the observed frequency of two-person pairings to (ii) the frequency expected by chance,

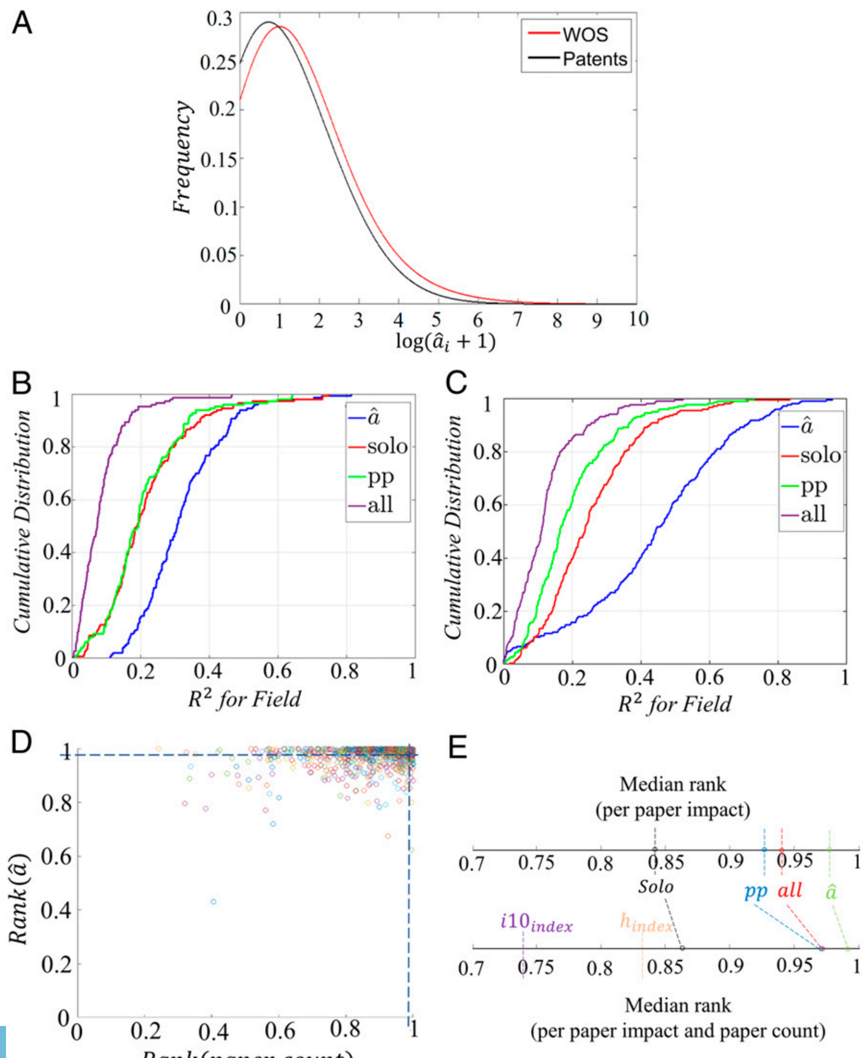

Fig. 4. Individual citation index. (*A*) The distributions of the individual citation index ($\hat{a}_i$) across Web of Science fields (red) and patenting fields (black). For paper or patent outcomes, the prediction of the citation impact for out-of-sample (*B*) solo-authored papers or (*C*) solo-invented patents. Predictive accuracy is measured in regressions, comparing the predictive capacity using $\hat{a}_i$ versus alternative measures (see text). The *x* axis presents the regression R^2 for a given field, and the *y* axis is the cumulative distribution across all fields. We see that $\hat{a}_i$ provides substantially more accurate predictions of out-of-sample citation outcomes compared with standard measures. For individual career outcomes, we rank each NAS member among that individual's corresponding cohort. (*D*) NAS members ranked by $\hat{a}_i$ (*y* axis) and publication count (*x* axis), with median ranks indicated by dashed lines. (*E*) Median rank for NAS members using alternative career metrics (see text). We see that $\hat{a}_i$ more accurately characterizes NAS members as high-rank individuals compared with standard career measures, including the h index.

drawing pairs of these individuals at random. We group individuals by mean citations to their solo work, rounded to the nearest integer. Fig. 3*A* shows a tendency toward assortative matching in the WOS, and Fig. 3*B* shows a similar tendency in patenting. Namely, collaborations are more frequent than expected by chance where $a_{high} = a_{low}$. Meanwhile, collaborations between individuals with different impact measures become increasingly unlikely as these differences become large.

We further deploy this analysis for each field separately within each domain. As a summary statistic, we examine the mean ratio of observed to expected frequencies where $a_{high} = a_{low}$ (i.e., we take the mean of the diagonal terms in matching matrices like Fig. 3 *A* and *B* but now analyzed by field). Fig. 3 *C* and *D* presents the distribution across fields for papers and patenting. In all fields, we see this mean ratio is greater than 1, so that positive assortative matching is a universal tendency. This tendency is consistent with the organizational implications of $\hat{\rho} < 1$. At the same time, teams may assemble this way for many reasons; for example, individuals with similar citation indices may sort into the same organizations or narrow subfields, which in turn facilitate their collaboration.

Our second group of results focuses on the individual citation index. The distribution of the individual index is right-skewed (Fig. 4*A*). These distributions are close to lognormal (*SI Appendix*, Fig. S3), which is consistent with citation distributions (29). The median individual citation index measure is $a_i = 1.32$ (papers) and $a_i = 1.05$ (patents), while the 95th percentile individual shows $a_i = 23.07$ (papers) and $a_i = 19.81$ (patents). Interestingly, we see a similar distributional shape in both the paper and patenting domains.

Notably, each individual citation index estimate has been determined accounting for the citation behavior of an individual's coauthors (and, more distantly, the citation behavior of everyone else in an individual's broader collaboration network). Moreover, these individual estimates are determined in light of the team-production parameters. An important implication of $\rho < 1$ is that the lower-ranked author is relatively important to the team-based outcome. Team-based outcomes will thus tend to be more informative about, and credit will accrue toward, the lower-index members of the team. By contrast, current popular methodologies for evaluating individuals (1) typically either are team blind (e.g., counting an individual's citations with no adjustment for team size, as in Google Scholar) or take a fractional approach (e.g., dividing citations by the number of coauthors), and promotion committees and funding panels are known to utilize such methods in evaluating individuals (30, 31) despite evidence that these may be poor predictors (32).

To examine the accuracy of the individual index estimates, $\hat{a}_i$, we consider their capacity to predict outcomes for out-of-sample papers and patents. Recall that $\hat{a}_i$ tells us the citation impact we expect for a paper or patent when the individual is a solo author or inventor. We run our estimations again for 100 WOS fields and 100 USPTO technology classes but leaving out, at random, one output from each individual. We then predict the outcome, y, for the paper or patent that was dropped. Further, we compare the predictive capacity of $\hat{a}_i$ against alternative, commonly used individual metrics (33), including (*i*) mean citations to the individual's works ("all," with no adjustment for the number of collaborators), (*ii*) mean citations per collaborator to the individual's works ("pp," with citations to each work are divided by its number of collaborators), and (*iii*) mean citations for the individual's solo works only ("solo"). A wide range of additional measures are analyzed in the *SI Appendix*, Tables S7 and S8. To measure prediction success, we run regressions by field, where the dependent variable is the citation impact of the out-of-sample work and the regressor is the predictive measure we are testing. We take the R^2 of each regression to capture goodness of fit. The *SI Appendix* provides further detail on methods.

Fig. 4*B* examines predictive success for out-of-sample solo-authored papers. Because these are solo-authored papers, the model prediction is $y_i = \hat{a}_i$, thus providing a focused test of the individual parameters. The figure presents the cumulative distribution of R^2 (across fields) for $\hat{a}_i$ and the common approaches *i–iii*. We see that the $\hat{a}_i$ estimates tend to provide substantially higher R^2 than the other metrics do in predicting out-of-sample outcomes. Notably, the model-estimated individual indices do better even than a simple average of the individuals' solo-authored works. The advantage of $\hat{a}_i$ comes because it is estimated using all of the individual's papers, which, although many involve team-authorship, help pin-down the measure. Fig. 4*C* shows that the estimates $\hat{a}_i$ similarly outperform the commonly used metrics when examining the patenting sphere. The *SI Appendix*, Table S8, shows that $\hat{a}_i$ similarly outperforms alternative metrics collected in (33), including numerous variants based on author order.

SI Appendix, Fig. S4, further considers out-of-sample prediction for works with two or three collaborators. Here the model prediction is based on the $\hat{a}_i$ for individuals in the team and the relevant $\hat{\beta}_n$ and $\hat{\rho}$ parameters for the field (estimated in samples where we have left out the papers or patents in the prediction set). The model prediction is then compared with predictions based on the popular constructs *i–iii* above. See *SI Appendix* for further discussion of methods. We again find large advantages of the model estimates in predicting out-of-sample outcomes, compared with these other measures. Overall, these findings suggest that our methodology, which can be applied in standard databases, can better predict outcomes both when individuals work alone and when they work in teams.

Our final results consider career outcomes. Here we consider an entire body of an individuals' work. Standard career metrics, such as the h index (34), incorporate paper impact measures and paper counts. In our context, the estimated $\hat{a}_i$ provides a per-paper impact measure for an individual, and we further incorporate publication volume, v_i, counting the papers the individual has joined in producing. As an outcome, we consider election to the National Academy of Sciences (NAS). We examine how NAS members rank among all other scholars in their cohort, defined as all individuals who share the same initial publication year and field (see *SI Appendix*, Tables S9 and S10, for data detail). Fig. 4*D* presents the ranks of $\hat{a}_i$ (vertical axis) and v_i (horizontal axis) for individuals elected to the NAS. NAS members rank at the 97th percentile of the $\hat{a}_i$ distribution and the 98th percentile of the v_i distribution, comparing against other scientists in their cohort.

How do these measures compare with standard career metrics? Prominent career metrics include (*i*) the h index (34), (*ii*) total citations received, and (*iii*) the i10 index, which counts an individual's papers with at least 10 citations. While these measures (all featured by Google Scholar) are team blind, other measures attempt to adjust for teamwork, including adjustments for the number of authors or author position (33). To assess these different approaches, we again rank NAS members against the other scientists in their field and cohort but now using these alternative metrics. Fig. 4*E* presents the median rank of individuals elected to the NAS for prominent alternatives. Additional comparisons are presented in the *SI Appendix*, Table S11. Using purely the per-paper impact measure (Fig. 4 *E*, *Top*) we see that ranking individuals based on $\hat{a}_i$ more accurately characterizes NAS members than alternative measures. Additionally, incorporating publication counts (Fig. 4 *E*, *Bottom*) further improves ranks. The $\hat{a}_i$-based rank continues to outperform. Notably, it proves far more accurate in characterizing NAS members than the h index. By contrast, total citations ("all") and equal sharing of citations per team member ("pp") do quite well (if not as well as using $\hat{a}_i$). This finding is consistent with the positive assortative matching we see above, where the tendency to work with teammates

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of similar individual citation indices can make equal credit per author systems relatively useful in ranking individuals.

Conclusion

We have presented a computationally feasible method for analyzing team and individual outcomes and deployed this methodology across large repositories of papers and patents. The analysis reveals universal patterns about team science and invention while providing a tool for estimating individual impact and predicting outcomes. The descriptive regularities suggest that team-based science and patenting most typically centers near the harmonic average of the team members' individual citation indices. These findings imply that team output is predicted more by the lower-index rather than the higher-index members of the team. This remarkable generality is further consistent with an observed tendency for team assembly among individuals with similar citation indices, which appears across all fields. Meanwhile, the individual index developed here is shown to outperform other metrics in predicting out-of-sample paper or patent outcomes and in characterizing eminent careers.

Further work can extend and refine this methodology and assess mechanisms. While our method, based on an individual fixed effect, is computationally feasible and can be deployed in available, wide-scale databases, in the context of richer data, extended methods might explore specific team assembly and production processes (4, 7, 10). Assessing choice in team assembly, sorting of ideas across teams, credit concerns, and effort allocation in idea production and marketing are important areas for future work. Causal research designs, including field and laboratory experiments, may allow close observation and isolation of specific mechanisms to help unpack the descriptive and predictive regularities unveiled here. In science fields that use author order (9, 35), one could further refine the methodology to study hierarchical roles (14), although our methodology already appears to outperform assessments that use author order (*SI Appendix*, Table S8). More generally, institutional features, such as the rise of postdoctoral positions and shifting funding landscapes, may interface with these findings, suggesting additionally important and policy-relevant avenues for future work. One may also extend this methodology by using alternative measures, beyond citation measures, to characterize outcomes, and by investigating teams in additional contexts. From entrepreneurship to songwriting, from surgery to sports, team assembly, team outcomes, and individual assessment are first-order concerns for the institutions that support teams and for the individuals themselves (13, 14, 36, 37).

Methods

The estimation produces two sets of parameters. First, we compute field-specific team-outcome parameters, $\hat{\rho}$ and $\hat{\beta}_2, \ldots, \hat{\beta}_n$. Second, we produce the individual index, $\hat{a}_i$, for every individual in the field, which can be hundreds of thousands of people. Because our outcome measure is the citations received by a given work, the estimate $\hat{a}_i$ is interpreted as an individual citation index. It represents the expected citation outcome for an output this person produces when working alone. Intuitively, the estimation of the individual citation index is possible because a person may sometimes work alone, providing a direct signal of his/her outcomes in that case, and/or because the same individual moves between different teams, allowing one to see how outcomes vary when a specific person is involved. In practice, for patents, we estimate the individual citation index for everyone in the technology class. For papers, very large fields in the WOS make estimation slow. In the largest 25 WOS fields, we therefore take, at random, a coauthor network within the field that contains between 50,000 and 100,000 unique authors. *SI Appendix*, Tables S1 and S2, presents the number of individuals analyzed for each field. Our estimation method is nonlinear least squares and should be interpreted as producing descriptive regularities and a tool for out-of-sample prediction, rather than isolating causative mechanisms. See *SI Appendix* for detailed discussion of methods; *SI Appendix* further describes the computational insights that make such a large-scale analysis feasible, demonstrates the successful convergence of the algorithm for widely different starting values in the parameter space, and demonstrates run times for collaboration networks of different size (*SI Appendix*, Tables S3–S5).

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