Quantifying Long-term Scientific Impact

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Abstract

An ability to accurately assess the long-term impact of a scientific discovery has implications from science policy to individual reward. Yet, the documented lack of predictability of citation based measures frequently used to gauge impact, from impact factors to short-term citations, raises a fundamental question: is there long-term predictability in citation patterns? Here we derive a mechanistic model for the citation dynamics of individual papers, allowing us to collapse the citation histories of papers from different journals and disciplines into a single curve, indicating that all papers follow the same universal temporal pattern. The observed patterns not only help us uncover the basic mechanisms that govern scientific impact, but also offer reliable measures of influence with potential policy implications.

Of the many tangible measures of scientific impact one stands out in its frequency of use: citations [1–9]. The reliance on citation based measures, from the Hirsch index [4] to the g-index [10], from impact factors [1] to eigenfactors [11], and on diverse ranking based metrics [12, 13], lies in the (often debated) perception that citations offer a quantitative proxy of a discovery's importance or a scientist's standing in the research community. In this debate it is often lost the fact that our ability to foresee lasting impact based on citation patterns has well-known limitations:

(i) The *impact factor* (IF) [1], conferring a journal's historical impact to a paper, is a poor predictor of a particular paper's future citations [14]: papers published in the same journal a decade later acquire widely different number of citations, from one to thousands (Fig. 1A).

(ii) The *number of citations* [2] collected by a paper strongly depends on the paper's age, hence citation based comparisons favor older papers and established investigators. It also lacks predictive power: a group of papers that within a five year span collect the same number of citations are found to have widely different long-term impact (Fig. 1B).

(iii) Paradigm changing discoveries have notoriously limited early impact [3], precisely because the more a discovery deviates from the current paradigm, the longer it takes to be appreciated by the community [15]. Indeed, while for most papers their early and long-term citations correlate, this correlation breaks down for discoveries with most long-term citations (Fig. 1C). Hence, publications with exceptional long-term impact appear to be the hardest to recognize based on their early citation patterns.

(iv) Comparison of different papers is confounded by incompatible publication/citation/acknowledgement traditions of different disciplines and journals.

These limitations not only affect science policy, but also probe our understanding of complex evolving systems [16–20], prompting us to ask, is there long-term predictability in such short-term measures as early citation patterns? To be sure, long-term cumulative measures like the Hirsch index have documented predictable components, that can be extracted via data mining [4, 21]. Yet, given the myriad of factors involved in the recognition of a new discovery, from the work's intrinsic value to timing, chance and the publishing venue, finding regularities in the citation history of *individual papers*, the minimal carriers of a scientific discovery, remains an elusive task.

The difficulty in identifying reproducible patterns in citation histories is well illustrated by the citation patterns of papers extracted from the Physical Review corpus (Fig. 1D), consisting of 463,348 papers published between 1893 and 2010 and spanning all areas of physics [3, 22, 23]. The fat tailed nature of the citation distribution 30 years after publication indicates that while most papers are hardly cited, a few do have exceptional impact (Fig. 1C inset) [2, 3, 8, 24, 25]. This impact heterogeneity, coupled with widely different citation histories (Fig. 1D), suggests a lack of order and hence lack of predictability in citation patterns. Yet, as we show next, this lack of order in citation histories is only apparent, as citations follow widely reproducible dynamical patterns that span research fields. Quantifying these patterns allow us to derive from first principles more accurate impact measures than the currently used heuristic quantities.

We start by identifying three fundamental mechanisms that drive the citation history of individual papers:

A) *Preferential attachment* captures the well-documented fact that highly cited papers are more visible and are more likely to be cited again than less-cited contributions [3, 20, 25, 26]. Accordingly a paper i's probability to be cited again is proportional to the total number of citations c_i the paper received previously. In Fig. 1E we document the presence of preferential attachment in our dataset as well.

B) *Aging* captures the fact that new ideas are integrated in subsequent work, hence each paper's novelty fades eventually [27–29]. The resulting long term decay is best described by a log-normal survival probability (see Fig. 1F and SM S2.1)

$$P_i(t) = \frac{1}{\sqrt{2\pi}\sigma_i t} \exp\left(-\frac{(\ln t - \mu_i)^2}{2\sigma_i^2}\right). \tag{1}$$

C) *Fitness*, η_i, captures the inherent differences between papers, accounting for the perceived novelty and importance of a discovery [19, 30, 31]. Novelty and importance depend on so many intangible and subjective dimensions that it is impossible to objectively quantify them all. Here we bypass the need to evaluate a paper's intrinsic value and view fitness η_i as a *collective measure capturing the community's response* to a work. As we show below, η_i can be extracted from a paper's citation history.

Combining A–C, we can write the probability that paper i is cited at time t after publication as

$$\Pi_i(t) \sim \eta_i c_i^t P_i(t). \tag{2}$$

Solving the associated master equation, Eq. (2) allows us to predict the cumulative number of citations acquired by paper i at time t after publication (SM S2.2)

$$c_i^t = m\left(e^{\frac{\beta\eta_i}{A}\Phi\left(\frac{\ln t-\mu_i}{\sigma_i}\right)} - 1\right), \tag{3}$$

where

$$\Phi(x) \equiv (2\pi)^{-1/2}\int_{-\infty}^{x} e^{-y^2/2}dy \tag{4}$$

is the cumulative normal distribution and m, β and A are global parameters. Equation (3) represents a minimal citation (MiC) model, that captures all known quantifiable mechanisms that affect citation histories. It predicts that the citation history of paper i is characterized by three fundamental parameters: the *relative fitness* $\lambda_i \equiv \eta_i\beta/A$, capturing a paper's importance relative to other papers; the *immediacy* μ_i, governing the time for a paper to reach its citation peak and the *longevity* σ_i, capturing the decay rate. Using the rescaled variables $\tilde{t} \equiv (\ln t - \mu_i)/\sigma_i$ and $\tilde{c} \equiv \ln(1 + c_i^t/m)/\lambda_i$, we obtain our main result,

$$\tilde{c} = \Phi(\tilde{t}), \tag{5}$$

predicting that each paper's citation history should follow the same universal curve $\Phi(\tilde{t})$ if rescaled with the paper-specific $(\lambda_i, \mu_i, \sigma_i)$ parameters. Given the obvious diversity of citation histories (Fig. 1D), this prediction is somewhat unexpected.

To test the validity of (5) we first determined (λ, μ, σ) for four papers selected for their widely different citation histories (Fig. 1G), finding that after rescaling they all collapse into a single curve (5) (Fig. 1H). The reason is explained in Fig. 1I: by varying λ, μ and σ, Eq. (3) can account for a wide range of empirically observed citation histories, from jump-decay patterns to delayed impact. Yet, to test the validity of MiC, we rescaled all papers published between 1950 and 1980 in the Physical Review corpus, finding that they all collapse into (5) (Fig. 1J). We also tested our model on all papers published in 1990 by 12 prominent journals (Table S2), finding an excellent collapse for all (see Fig. 1J inset for Science and SM S2.4 for the other journals). The data collapse demonstrates that the observed differences in individual citation histories (Fig 1D,G) are rooted in variations in three measurable parameters: fitness, immediacy and longevity. Hence the diverse citation histories hide a remarkable degree of regularity, accurately captured by the MiC model

(3)–(5).

The model (3)-(5) also predicts several fundamental measures of impact:

Ultimate impact (c^{∞}) represents the total number of citations a paper acquires during its lifetime. By taking the $t \to \infty$ limit in Eq. (3), we obtain

$$c_i^{\infty} = m \left(e^{\lambda_i} - 1 \right), \tag{6}$$

a simple formula that predicts that the total number of citations acquired by a paper during its lifetime is independent of immediacy (μ) or the rate of decay (σ), and *depends only on a single parameter, the paper's relative fitness*, λ.

Impact time (T_i^*) represents the characteristic time it takes for a paper to collect the bulk of its citations. A natural measure is the time necessary for a paper to reach the geometric mean of its final citations, obtaining (SM S2.2)

$$T_i^* \approx \exp(\mu_i). \tag{7}$$

Hence impact time is mainly determined by the immediacy parameter μ_i and is independent of fitness λ_i or decay σ_i.

The MiC model offers a journal free methodology to evaluate long term impact. To illustrate this we selected three journals with widely different IFs: *Physical Review B* (*PRB*) (IF = 3.26 in 1992), *PNAS* (10.48) and *Cell* (33.62), and measured for each paper published by them the fitness λ, obtaining their distinct journal-specific $P(\lambda)$ fitness distribution (Fig. 2A). We then selected all papers with comparable fitness $\lambda \approx 1$, and followed their citation histories. As expected they follow different paths: *Cell* papers ran slightly ahead and *PRB* papers stay behind, resulting in distinct $P(c^T)$ distributions for years $T = 2 \div 4$. Yet, by year 20 the cumulative number of citations acquired by these papers show a remarkable convergence to each other (Fig. 2B), supporting our prediction that given their similar fitness λ, eventually they will have the same ultimate impact $c^{\infty} = 51.5$. This convergence is also supported by the decreasing $\sigma_c / \langle c \rangle$ ratio of $P(c^T)$ (Fig. 2C), indicating that the differences in citation counts between these papers vanish with time. In contrast, if we choose all papers with the same number of citations at year two (i.e. the same c^2, Fig. 2D), the citations acquired by them diverge with time and $\sigma_c / \langle c \rangle$ increases (Fig. 2E,F), supporting the lack of predictability in these quantities. Therefore λ and c^{∞} offer a journal independent measure of a publication's long-term impact, in contrast with the lack of predictive power of c^2 and/or the IF.

The model (3–5) also helps connect the impact factor, the traditional measure of impact of a scientific journal, to the journal's Λ, M, and Σ parameters (the analogs of λ, μ, σ, S4),

$$\mathrm{IF} \approx \frac{m}{2}\left(\exp\left[\Lambda\Phi\left(\frac{M_1 - M}{\Sigma}\right)\right] - \exp\left[\Lambda\Phi\left(\frac{M_2 - M}{\Sigma}\right)\right]\right). \tag{8}$$

Knowing Λ, in analog with (6) we can calculate a journal's ultimate impact as $C^{\infty} = m\left(e^{\Lambda} - 1\right)$, representing the total number of citations a paper in the journal will receive during its lifetime. Equation (8) helps us understand the mechanisms that influence changes in the IF, as vividly illustrated by the evolution of *Cell* and *NEJM*: in 1998 the IFs of *Cell* and *NEJM* were 38.7 and 28.7, respectively (Fig. 3A). Yet over the next decade there was a remarkable reversal: *NEJM* became the first journal to reach IF = 50, while *Cell*'s IF decreased to around 30. This raises a puzzling question: has the impact of papers published by the two journals changed so dramatically? To answer this we determined Λ, M, and Σ for both journals from 1996 to 2006 (Fig. 3D–F). While Σ were indistinguishable (Fig. 3D), we find that the fitness of *NEJM* increased from $\Lambda = 2.4$ (1996) to $\Lambda = 3.33$ (2005), increasing the journal's ultimate impact from $C^{\infty} = 300$ (1996) to a remarkable $C^{\infty} = 812$ (2005) (Fig. 3B). But *Cell*'s Λ also increased in this period (Fig. 3E), moving its ultimate impact from $C^{\infty} = 366$ (1996) to 573 (2005). Yet, if both journals attracted papers with increasing long-term impact, why did *Cell*'s IF drop and *NEJM*'s grow? The answer lies in changes in the impact time $T^* = \exp(M)$: while *NEJM*'s impact time remained unchanged at $T^* \approx 3$ years, *Cell*'s T^* increased from $T^* = 2.4$ years to $T^* = 4$ years (Fig. 3C). Therefore, *Cell* papers have gravitated from short to long-term impact: a typical *Cell* paper gets 50% more citations than a decade ago, but fewer of the citations come within the first two years (Fig. 3C, inset). In contrast, with a largely unchanged T^*, *NEJM*'s increase in Λ translated into a higher IF. These conclusions are fully supported by the $P(\lambda)$ and $P(\mu)$ distributions for individual papers published by *Cell* and *NEJM* in 1996 and 2005: both journals show a clear shift to higher fitness papers (Fig. 3G), but while $P(\mu)$ is largely unchanged for *NEJM*, there is a clear shift to higher μ papers in *Cell* (Fig. 3H).

While our primary goal is to uncover the mechanisms driving a paper's citation history, the accuracy of the MiC model raises a tantalizing question: can we use the developed framework to predict the future citations of a publication? In principle we can use paper i's citation history up to year T_{Train} after publication (training period) to estimate λ_i, μ_i, σ_i and then use Eq. (3) to predict its future citations c_i^t or (6) to determine its ultimate impact c_i^∞. Yet, the uncertainties in estimating λ_i, μ_i, σ_i from the inherently noisy citation histories affect our predictive accuracy (see SM S2.6). Hence instead of simply interpolating Eq. (3) into the future, we assign a citation envelope to each paper, quantifying the uncertainty of our predictions (see S2.6). In Fig. 4A, we show the predicted most likely citation path (red line) with the uncertainty envelope (grey area) for three papers, based on a 5 year training period. Two of the three papers fall within the envelope, for the third, however, the MiC model overestimates the future citations. Increasing the training period enhances the predictive accuracy (Fig. 4B).

To quantify the model's overall predictive accuracy we measure the fraction of papers that fall within the envelope for all PR papers published in 1960s. That is, we measure the z_{30}-score for each paper, capturing the number of standard deviations z_{30} the real citations c^{30} deviate from the most likely citation 30 years after publication. The obtained $P(z_{30})$ distribution across all papers decays fast with z_{30} (Fig. 4C), indicating that large z values are extremely rare. With $T_{Train} = 5$ only 6.5% of the papers leave the prediction envelope 30 years later, hence the model correctly approximates the citation range for 93.5% of papers 25 years into the future.

The observed accuracy prompts us to ask whether MiC is unique in its ability to capture future citation histories. We therefore identified several models that have been either used in the past to fit citation histories, or have the potential to do so (Table 1). We fit the predictions of these models to PR papers and use the weighted Kolmogorov-Smirnov (KS) test to evaluate their goodness of fit (see S3.2). The lowest KS distribution (indicating the best fit across most papers, Fig. 4D) is offered by Eq. (3). The reason is illustrated in Fig. S11: the symmetric $c(t)$ predicted by the Logistic Model cannot capture the asymmetric citation curves. While the Gompertz and the Bass models predict asymmetric citation patterns, they also predict an exponential (Bass) or double-exponential (Gompertz) decay of citations (Table 1), much faster than observed in real data. To see how these deviations affect the predictive power of these models, we used a 5 and a 10 year training period to fit the parameters of each model and computed the predicted most likely citations at year 30

(Fig. 4E,F). We find that independent of the training period the predictions of the Logistic, Bass and Gompertz models always lay outside the 25%–75% prediction quartiles (red bars), systematically underestimating future citations. In contrast, the prediction of Eq. (3) for both training periods is within the 25-75% quantiles, its accuracy visibly improving for the ten year training period (Fig. 4F). The predictive limitations of the current models is also captured by their $P(z_{30})$ distribution, indicating that for the Logistic, Bass and Gompertz model more than half of the papers underestimate with more than two standard deviations the true citations ($z > 2$) at year 30 (Fig. 4C), in contrast with 6.5% for the MiC model.

The remarkable accuracy of the MiC model, both in its ability to capture the universal aspects of citation histories, as well as to predict future citations, indicates that scientific impact is a collective phenomenon, governed by mechanisms that follow reproducible patterns [18, 32, 33]. Therefore the proposed modeling framework is not limited to citations, but with appropriate adjustments will likely apply to other phenomena driven by collective processes, from patents to the popularity of twitter hash tags. Yet, the model has obvious limitations: it cannot account for exogenous "second acts", like the citation bump observed for superconductivity papers following the discovery of high temperature superconductivity in the 1980s, or delayed impact, like the explosion of citations to Erdős and Rényi's work four decades after their publication, following the emergence of network science [3, 16, 19, 20].

Taken together, the mechanistic understanding of citation dynamics offers a quantitative springboard to uncover the hallmarks of future impact. These questions also have major policy implications, as current measures of citation-based impact, from IF to Hirsch index [4, 21], are frequently integrated in reward procedures, the assignment of research grants, awards and even salaries and bonuses [34, 35], despite their well-known lack of predictive power. In contrast with the IF and short-term citations that lack predictive power, we find that c^{∞} offers a journal independent assessment of a paper's long term impact, with a meaningful interpretation: it captures the total number of citations a paper will ever acquire, or the discovery's ultimate impact. While additional variables combined with data mining could further enhance the demonstrated predictive power, an ultimate understanding of long-term impact will benefit from a mechanistic understanding of the factors that govern the research community's response to a discovery.

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Figure 1: **Characterizing citation dynamics**. (A) Distribution of the cumulative citations ten years after publication (c^{10}) for all papers published in *Cell*, *PNAS*, and *Physical Review B* (*PRB*) in 1990. (B) Citation history of all papers shown in (A) that acquired 50 citations 5 years after publication, illustrating the different long-term impact despite their equal early impact. (C) Average number of citations acquired two years after publication (c^2) for papers with the same long-term impact (c^{30}), indicating that for high impact papers ($c^{30} \geq 400$, shaded area) the early citations underestimate future impact. Inset: Distribution of citations 30 years after publication (c^{30}) for PR papers published between 1950 and 1980. (D) Yearly citation $c_i(t)$ for 200 randomly selected papers published between 1960 and 1970 in the Physical Review (PR) corpus. The color code corresponds to each papers' publication year. (E) Attachment rate measures the likelihood for new papers published in different years (color coded) to cite an old paper with c^t citations. That is, for each year, c^t measures the citations of each paper before this year, and attachment rate measures the average number of times each paper with c^t citations was cited in this year. The linearity of the curves offer evidence for preferential attachment. (F) Distribution of papers' age when they get cited. To separate the effect of preferential attachment, we measure the aging function for papers with the same number of previous citations (here $c^t = 20$, see also S2.1). The solid line corresponds to gaussian fit of the data, indicating $P(\ln \Delta t \mid c^t)$ follows a normal distribution. (G) Citation history of four papers published in PR in 1964, selected for their distinct dynamics, displaying a 'jump-decay' pattern (blue); delayed peak (magenta); attracting a constant number of citation over time (green), or acquiring an increasing number of citations each year (red). (H) Data collapse for the four papers in (G) using Eq. (5). Legend: the (λ, μ, σ) parameters used to rescale the citation history of each paper. (I) Changes in the citation history $c(t)$ according to (3) after varying the (λ, μ, σ) parameters, indicating that (3) can account for a wide range of citation patterns. (J) Data collapse for 7,775 papers with more than 30 citations within 30 years in the PR corpus published between 1950 and 1980. Inset: data collapse for the 20 year citation histories of all papers published by *Science* in 1990 (842 papers).

Figure 2: **Evaluating long-term Impact**. (A) Fitness distribution $P(\lambda)$ for papers published by *Cell*, *PNAS*, and *Physical Review B* (*PRB*) in 1990. Shaded area indicates papers in the $\lambda \approx 1$ range selected for further study. (B) Citation distributions for papers with fitness $\lambda \approx 1$ highlighted in (A) for years 2, 4, 10, and 20 after publication. (C) Time

dependent relative variance of citations for papers selected in (A). (D) Citation distribution two years after publication ($P(c^2)$) for papers published by *Cell*, *PNAS*, and *PRB*. Shaded area highlights papers with $c^2 \in [5, 9]$ selected for further study. (E) Citation distributions for papers with $c^2 \in [5, 9]$ selected in (D) after 2, 4, 10, and 20 years. (F) Time dependent relative variance of citations for papers selected in (D).

Figure 3: **Quantifying changes in a journal's long-term impact**. (A) Impact factor of *Cell* and *New England Journal of Medicine* (*NEJM*) reported by Thomson Reuters from 1998 to 2006. (B) Ultimate impact C^∞ (see Eq. (6)) of papers published by the two journals from 1996 to 2005. (C) Impact time T^* (Eq. (7)) of papers published by the two journals from 1996 to 2005. Inset: fraction of citations that contribute to the IF. (D–F) The measured time dependent longevity (Σ), fitness (Λ), and immediacy (M) for the two journals. (G) Fitness distribution for individual papers published by *Cell* (left) and *NEJM* (right) in 1996 (black) and 2005 (red). (H) Immediacy distributions for individual papers published by *Cell* (left) and *NEJM* (right) in 1996 (black) and 2005 (red).

Figure 4: **Predicting Future Citations**. (A, B) Prediction envelope for three papers obtained using a five (A) and ten (B) years of training (shaded vertical area). The middle curve offers an example of a paper for which the prediction envelope misses the future evolution of the citations. The envelope illustrates the range for which $z \leq 1$. Comparing A and B illustrates how the increasing training period decreases the uncertainty of the prediction, resulting in a narrower envelope. (C) Complementary cumulative distribution of z_{30} ($P^>(z_{30})$), where z_{30} quantifies how many standard deviations the predicted citation history deviates from the real citation curve thirty years after publication (see also S2.6). We selected papers published in 1960s in PR corpus that acquire at least 10 citations in 5 years (4492 in total). The red curve captures predictions for 30 years after publication for $T_{Train} = 10$, indicating that for the MiC model 93.5% papers have $z_{30} \leq 2$. The blue curve relies on 5 year training. The grey curves capture the predictions of Gompertz (solid line), Bass (dash-dot line), and Logistic (dotted line) model for 30 years after publication by using 10 years as training. (D) Goodness of fit using weighted Kolmogorov-Smirnov (KS) test (see S3.2), indicating that Eq. (3) offers the best fit to our testing base (same as the papers in C) (E, F) Scatter plots of predicted citations and real citations at year 30 for our test base (same sample as in C, D), using as training data the citation history for the first 5 (E) or 10 (F) years. The error bars indicate prediction quartiles (25% and 75%) in each bin, and

are colored green if $y = x$ lies between the two quartiles in that bin, and red otherwise. The black circles correspond to the average predicted citations in that bin.

[1] E. Garfield. The history and meaning of the journal impact factor. *JAMA: the journal of the American Medical Association*, 295(1):90–93, 2006.

[2] D.J. de Solla Price. Networks of scientific papers. *Science*, 149(3683):510–515, 1965.

[3] S. Redner. Citation statistics from 110 years of physical review. *Physics Today*, 58:49, 2005.

[4] J.E. Hirsch. An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United states of America*, 102(46):16569, 2005.

[5] S. Lehmann, A.D. Jackson, and B.E. Lautrup. Measures for measures. *Nature*, 444(7122): 1003–1004, 2006.

[6] S. Wuchty, B.F. Jones, and B. Uzzi. The increasing dominance of teams in production of knowledge. *Science*, 316(5827):1036–1039, 2007.

[7] B.F. Jones, S. Wuchty, and B. Uzzi. Multi-university research teams: shifting impact, geography, and stratification in science. *Science*, 322(5905):1259–1262, 2008.

[8] F. Radicchi, S. Fortunato, and C. Castellano. Universality of citation distributions: Toward an objective measure of scientific impact. *Proceedings of the National Academy of Sciences*, 105(45):17268–17272, 2008.

[9] J.A. Evans and J.G. Foster. Metaknowledge. *Science*, 331(6018):721–725, 2011.

[10] L. Egghe. Theory and practise of the g-index. *Scientometrics*, 69(1):131–152, 2006.

[11] A. Fersht. The most influential journals: Impact factor and eigenfactor. *Proceedings of the National Academy of Sciences*, 106(17):6883–6884, 2009.

[12] P. Chen, H. Xie, S. Maslov, and S. Redner. Finding scientific gems with googles pagerank algorithm. *Journal of Informetrics*, 1(1):8–15, 2007.

[13] F. Radicchi, S. Fortunato, B. Markines, and A. Vespignani. Diffusion of scientific credits and the ranking of scientists. *Physical Review E*, 80(5):056103, 2009.

[14] P.O. Seglen. Why the impact factor of journals should not be used for evaluating research. *BMJ: British Medical Journal*, 314(7079):498, 1997.

[15] T.S. Kuhn. *The structure of scientific revolutions.* University of Chicago press, 1996.

[16] R. Cohen and S. Havlin. *Complex networks: structure, robustness and function.* Cambridge University Press, 2010.

[17] C. Castellano, S. Fortunato, and V. Loreto. Statistical physics of social dynamics. *Reviews of*

Modern Physics, 81(2):591, 2009.

[18] T. Vicsek and A. Zafeiris. Collective motion. *Physics Reports*, 517:71–140, 2012.

[19] S.N. Dorogovtsev and J.F.F. Mendes. *Evolution of networks: From biological nets to the Internet and WWW.* Oxford, 2003.

[20] G. Caldarelli. *Scale-Free Networks.* Oxford University Press, 2007.

[21] D.E. Acuna, S. Allesina, and K.P. Kording. Future impact: Predicting scientific success. *Nature*, 489(7415):201–202, 2012.

[22] S. Lehmann, B. Lautrup, and AD Jackson. Citation networks in high energy physics. *Physical Review E*, 68(2):026113, 2003.

[23] F. Radicchi, S. Fortunato, and A. Vespignani. Citation networks. *Models of Science Dynamics*, pages 233–257, 2012.

[24] S. Redner. How popular is your paper? an empirical study of the citation distribution. *The European Physical Journal B*, 4(2):131–134, 1998.

[25] A.-L. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286(5439): 509–512, 1999.

[26] H.A. Simon. On a class of skew distribution functions. *Biometrika*, pages 425–440, 1955.

[27] M. Medo, G. Cimini, and S. Gualdi. Temporal effects in the growth of networks. *Physical Review Letters*, 107(23):238701, 2011.

[28] S.N. Dorogovtsev and J.F.F. Mendes. Evolution of networks with aging of sites. *Physical Review E*, 62(2):1842, 2000.

[29] D. Walker, H. Xie, K.K. Yan, and S. Maslov. Ranking scientific publications using a model of network traffic. *Journal of Statistical Mechanics: Theory and Experiment*, 2007(06):P06010, 2007.

[30] G. Bianconi and A.-L. Barabási. Competition and multiscaling in evolving networks. *EPL (Europhysics Letters)*, 54:436, 2001.

[31] G. Caldarelli, A. Capocci, P. De Los Rios, and M.A. Muñoz. Scale-free networks from varying vertex intrinsic fitness. *Physical Review Letters*, 89(25):258702, 2002.

[32] F. Cecconi, M. Marsili, J.R. Banavar, and A. Maritan. Diffusion, peer pressure, and tailed distributions. *Physical Review Letters*, 89(8):88102, 2002.

[33] R.V. Solé, R. Ferrer-Cancho, J.M. Montoya, and S. Valverde. Selection, tinkering, and emergence in complex networks. *Complexity*, 8(1):20–33, 2003.

[34] A. Mazloumian, Y.H. Eom, D. Helbing, S. Lozano, and S. Fortunato. How citation boosts promote scientific paradigm shifts and Nobel prizes. *PloS one*, 6(5):e18975, 2011.

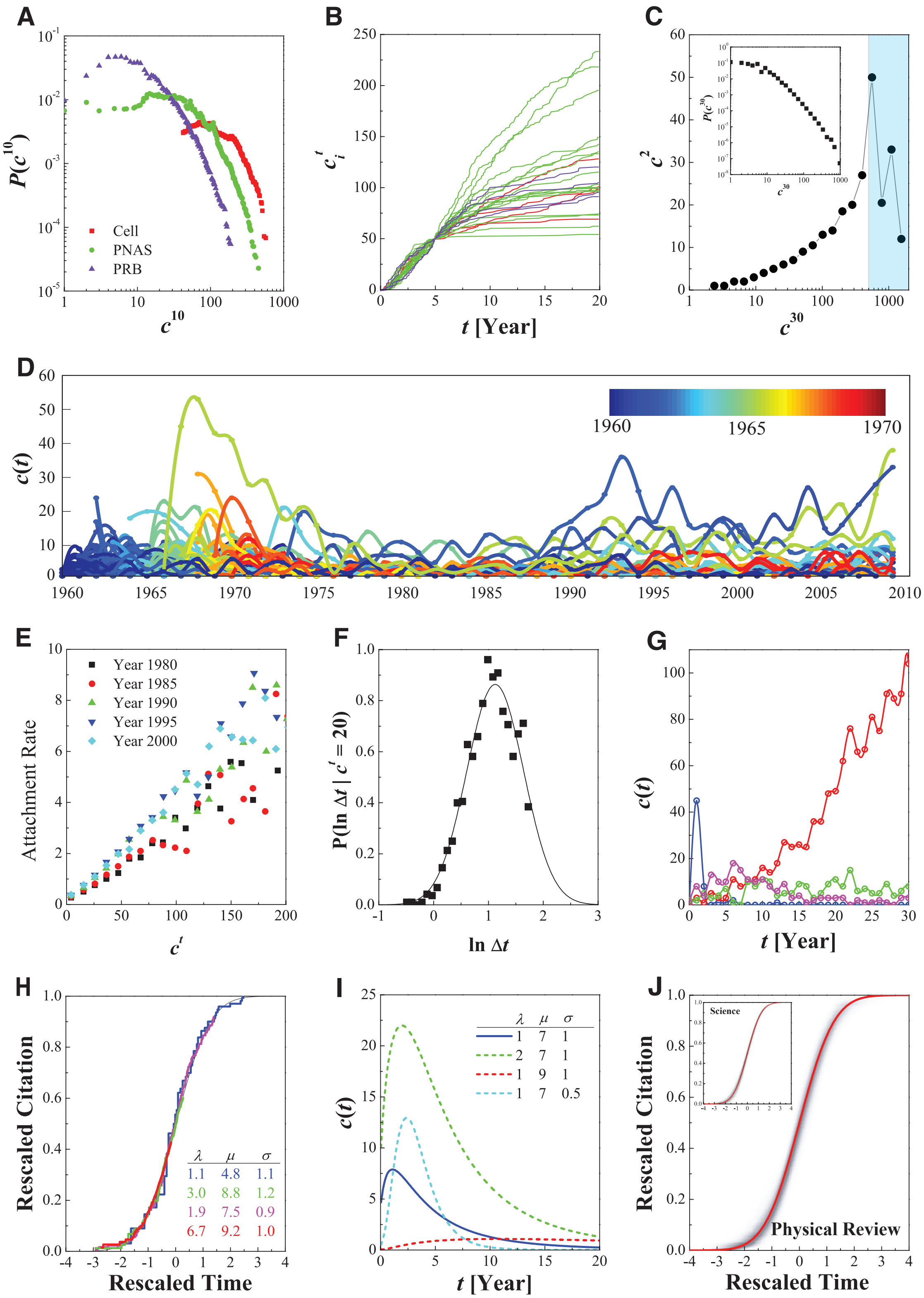
[35] I. Fuyuno and D. Cyranoski. Cash for papers: Putting a premium on publication. *Nature*, 441(7095):792, 2006.

[36] V. Mahajan, E. Muller, and F.M. Bass. New product diffusion models in marketing: A review and directions for research. *The Journal of Marketing*, pages 1–26, 1990.

[37] F.M. Bass. Comments on "a new product growth for model consumer durables the bass mode". *Management science*, 50(12):1833–1840, 2004.

[38] Benjamin Gompertz. On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. *Philosophical transactions of the Royal Society of London*, 115:513–583, 1825.

FIGURES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Science
Physical Review

FIG. 1

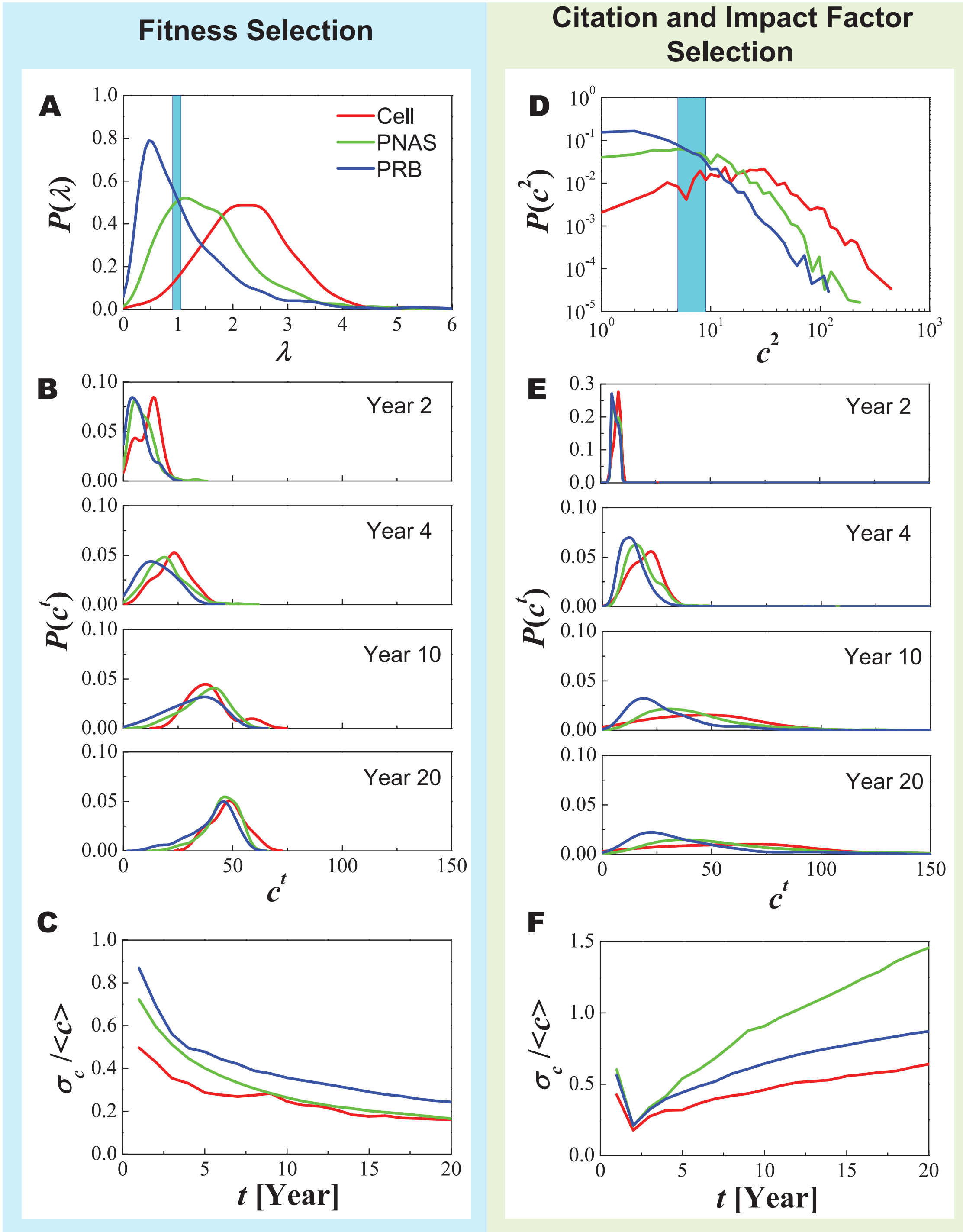
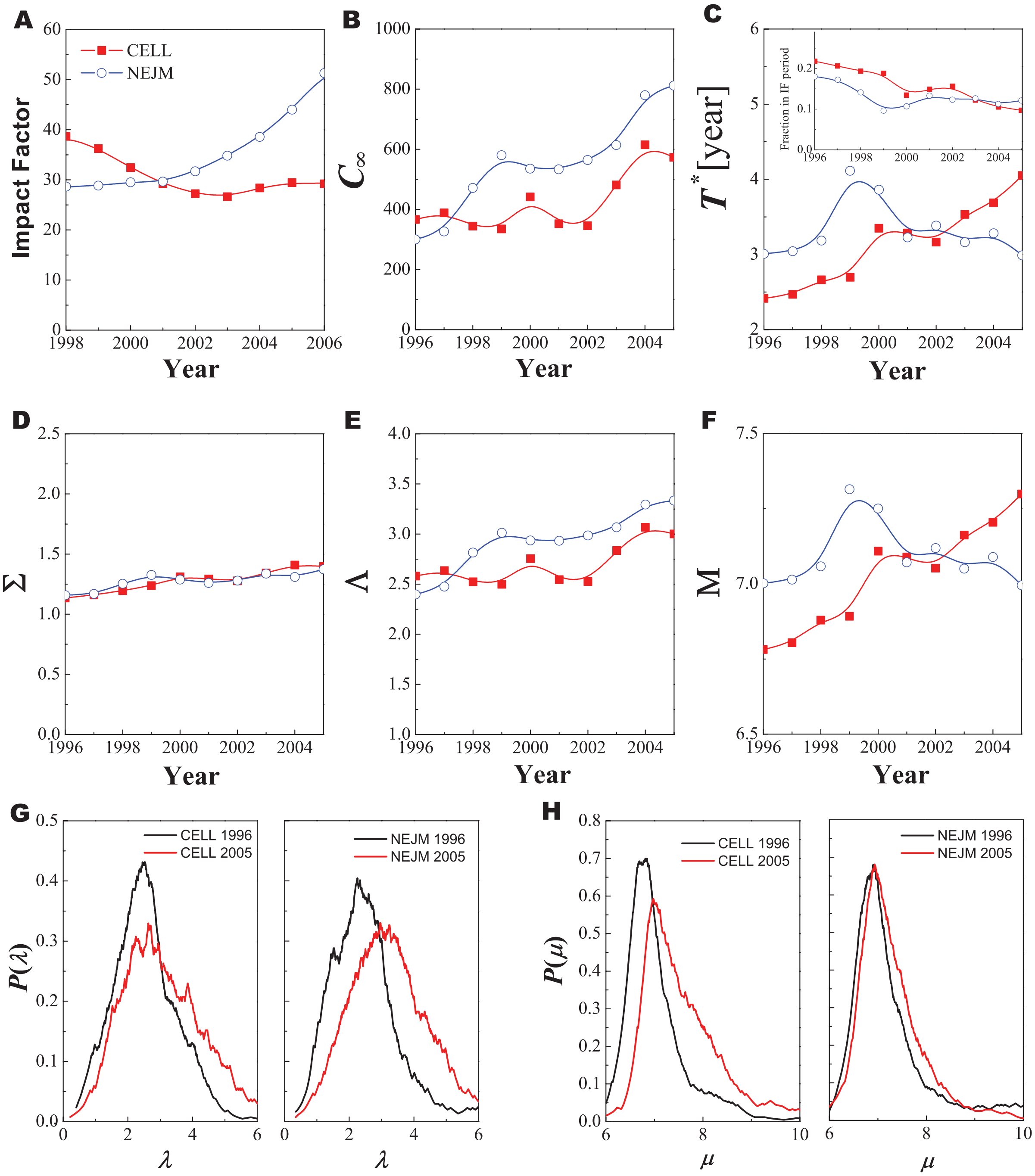

Fitness Selection
Citation and Impact Factor Selection
A
Cell
PNAS
PRB
B
Year 2
Year 4
Year 10
Year 20
C
D
E
F
t [Year]

FIG. 2



A
CELL
NEJM
Impact Factor
Year
B
C_∞
Year
C
T^* [year]
Fraction in IF period
Year
D
Σ
Year
E
Λ
Year
F
M
Year
G
CELL 1996
CELL 2005
NEJM 1996
NEJM 2005
$P(\lambda)$
λ
H
CELL 1996
CELL 2005
NEJM 1996
NEJM 2005
$P(\mu)$
μ

FIG. 3

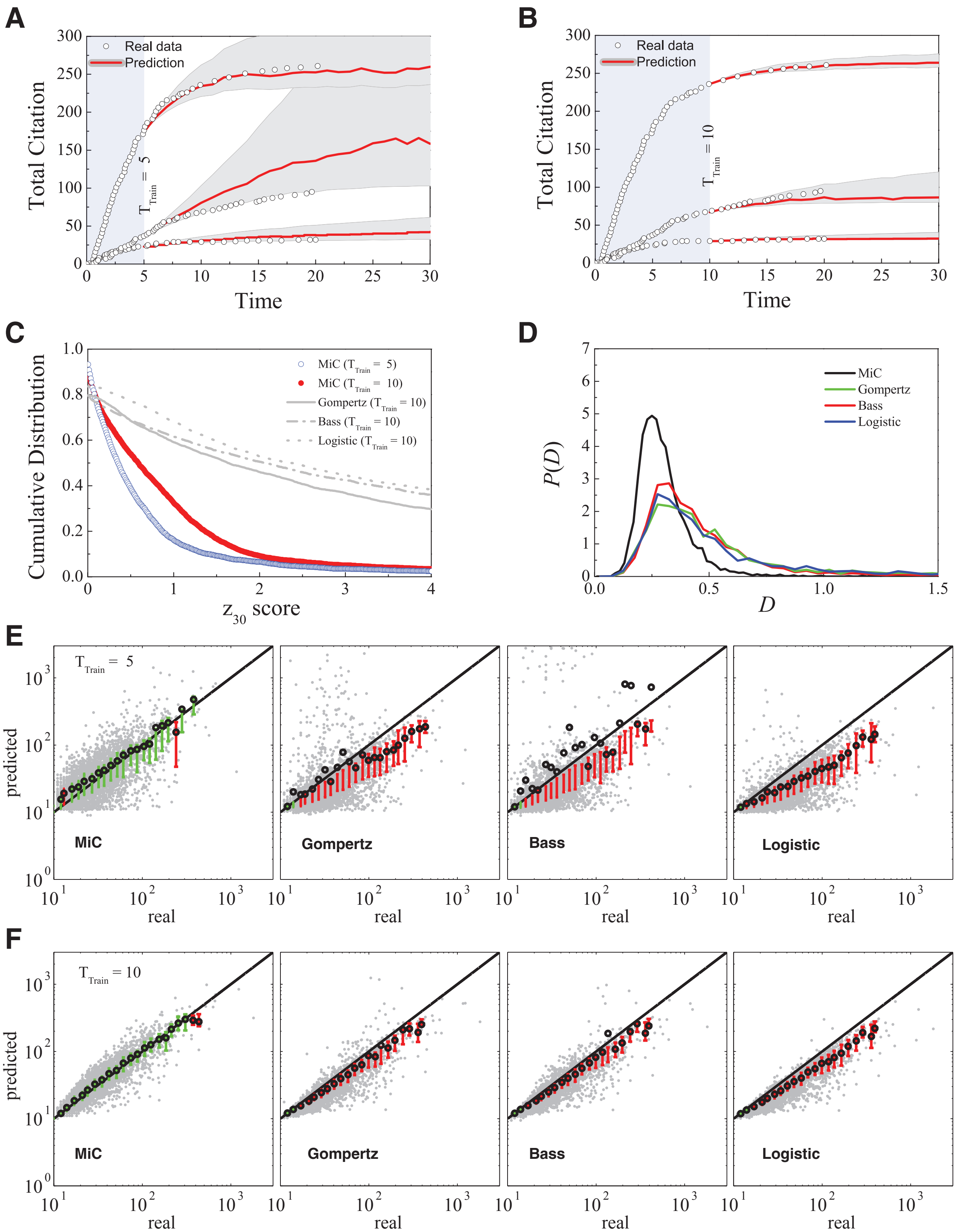

A
B
C
D
E
F
Real data
Prediction
Total Citation
Time
T_{Train} = 5
T_{Train} = 10
Cumulative Distribution
z_{30} score
MiC (T_{Train} = 5)
MiC (T_{Train} = 10)
Gompertz (T_{Train} = 10)
Bass (T_{Train} = 10)
Logistic (T_{Train} = 10)
$P(D)$
D
MiC
Gompertz
Bass
Logistic
predicted
real

FIG. 4

TABLES

TABLE I: **Modeling citation dynamics**. We identified four models that can be or have been used to fit citation histories. The table shows the corresponding rate equation and its analytical solution. The models and the meaning of their parameters in each model are described in S3. In the manuscript we did not test the prediction of the BB model, as it lacks saturation for high t, hence it is unable to fit true citation histories.

Abbr.	**Model Name**	**Rate Equation**	**Solution**
MiC	Minimal Citation Model, Eq. (3)	$\frac{dc_i^t}{dt} \approx c_i^t \eta_i P(t)$	$c_i^t = m\left(e^{\lambda_i \Phi(\frac{\ln t - \mu_i}{\sigma_i})} - 1\right)$
BB	Bianconi-Barabási [30]	$\frac{dc_i^t}{dt} \approx \eta_i c_i^t$	$c_i^t \sim \exp(\lambda_i t)$
LOG	Logistic [36]	$\frac{dc_i^t}{dt} = r_i c_i^t \left(1 - c_i^t/c^\infty\right)$	$c_i^t = \frac{c^\infty}{1+e^{-r_i(t-\tau_i)}}$
B	Bass [37]	$\frac{dc_i^t}{dt} = (p + qc_i^t/c^\infty)(c^\infty - c_i^t)$	$c_i^t = c^\infty \frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}}$
G	Gompertz [36, 38]	$\frac{dc_i^t}{dt} = qc_i^t \ln(c^\infty/c_i^t)$	$c_i^t = c^\infty e^{-e^{-(a+qt)}}$