## Supplementary Material

# The Memory of Science: Inflation, Myopia, and the Knowledge Network

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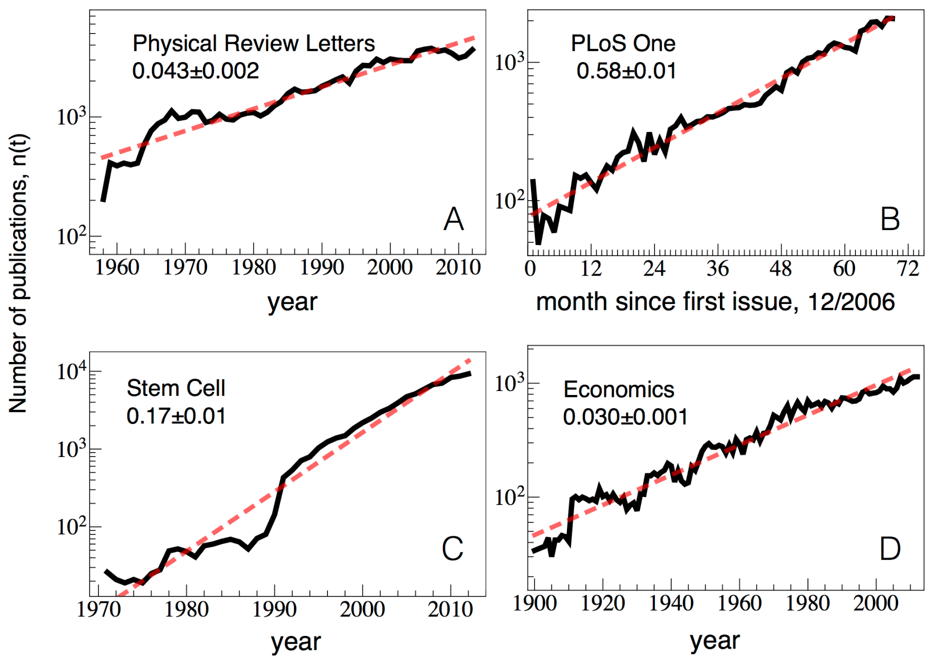


FIG. S1: **Empirical growth of scientific output: journals, fields** (A,B) Growth in two specific journals. Physical Review Letters (physics), and PLoS One (multidisciplinary open access). The remarkable growth rate for PLoS One – representative of the open-access shift in scientific publication – dwarfs the others by an entire order of magnitude, with the annual growth rate $0.58$ corresponding to a publication doubling rate of $\ln 2/0.58 = 1.2$ years. (C,D) Disciplinary-specific publication growth for Stem Cell research and an aggregation of 14 high-impact economics journals (American Economic Review, Econometrica, Journal of Political Economy, Journal of Economic Theory, Journal of Econometrics, Journal of Financial Economics, Journal of Finance, Journal of Economic Growth, Journal of Economic Perspectives, Journal of Economic Literature, Quarterly Journal of Economics, Review of Economic Studies, Review of Financial Studies, Review of Economics and Statistics). "Stem Cell" articles were queried and collected from TR. This research area indicates how the growth of subfields can be nonlinearly perturbed by transformative discoveries possibly leading to subsequent directed funding into the field which further drives growth.

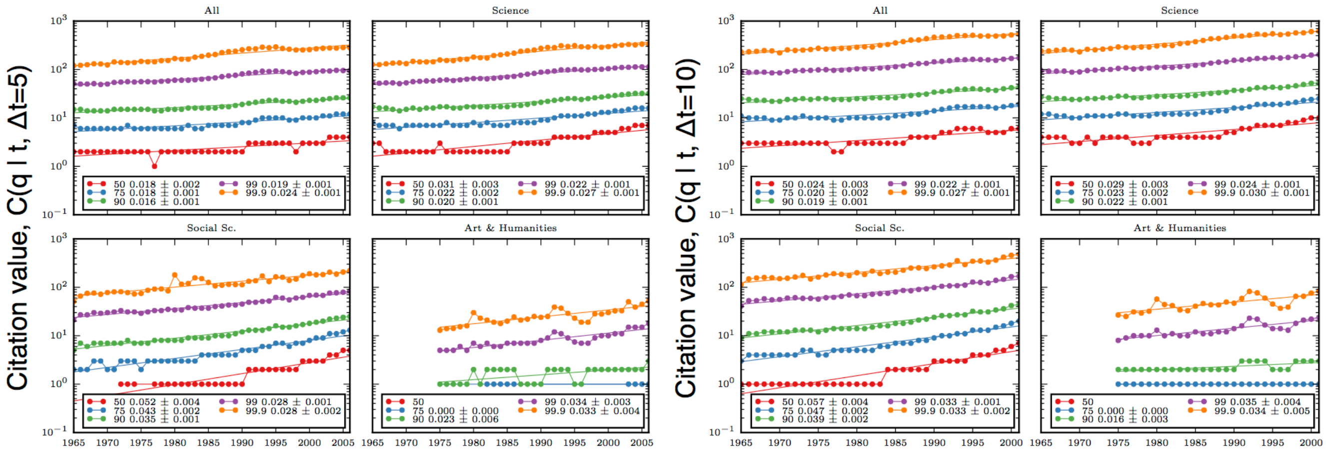


FIG. S2: **Inflation of the number of citations received and corresponding to various citation distribution percentiles.** The citation value $C(q|t)$ corresponding to a given percentile $q$ of the citation distribution $P(c^p_{t,5})$ ($100{\times}q$ values shown in each panel legend with best-fit exponential growth parameter for each curve).

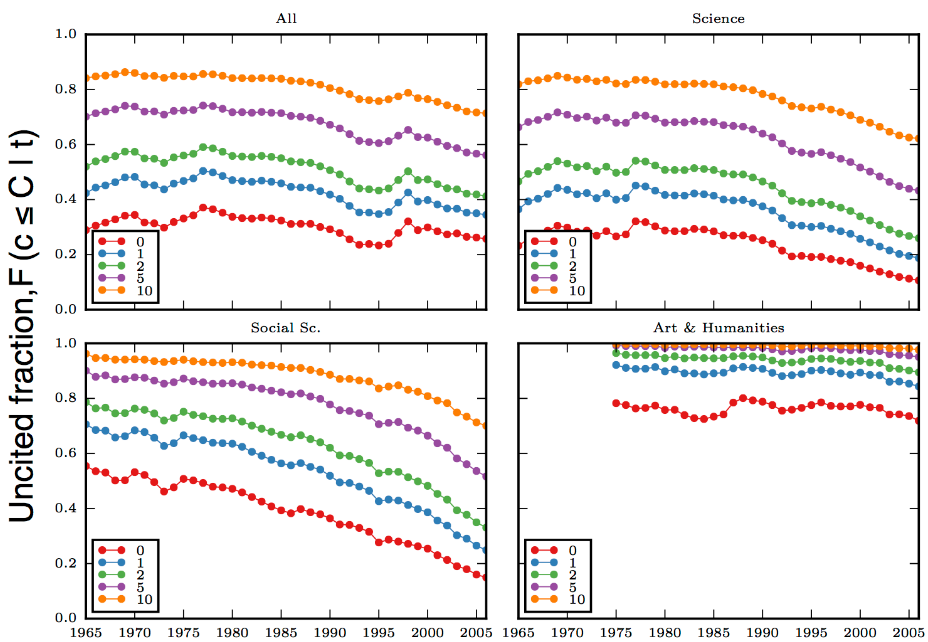


FIG. S3: **Empirical patterns of decreasing uncitedeness.** The fraction $F(c \leq C|t)$ of publications with $c^p_{t,5} \leq C$. The $C$ value thresholds for each curve are indicated in each panel legend. We do not observe the same decreasing trend for Arts & Humanities, which still has a large fraction of literature that goes relatively uncited, possibly due to the significantly slower growth in the total reference supply $R(t)$ (see Fig. S1).

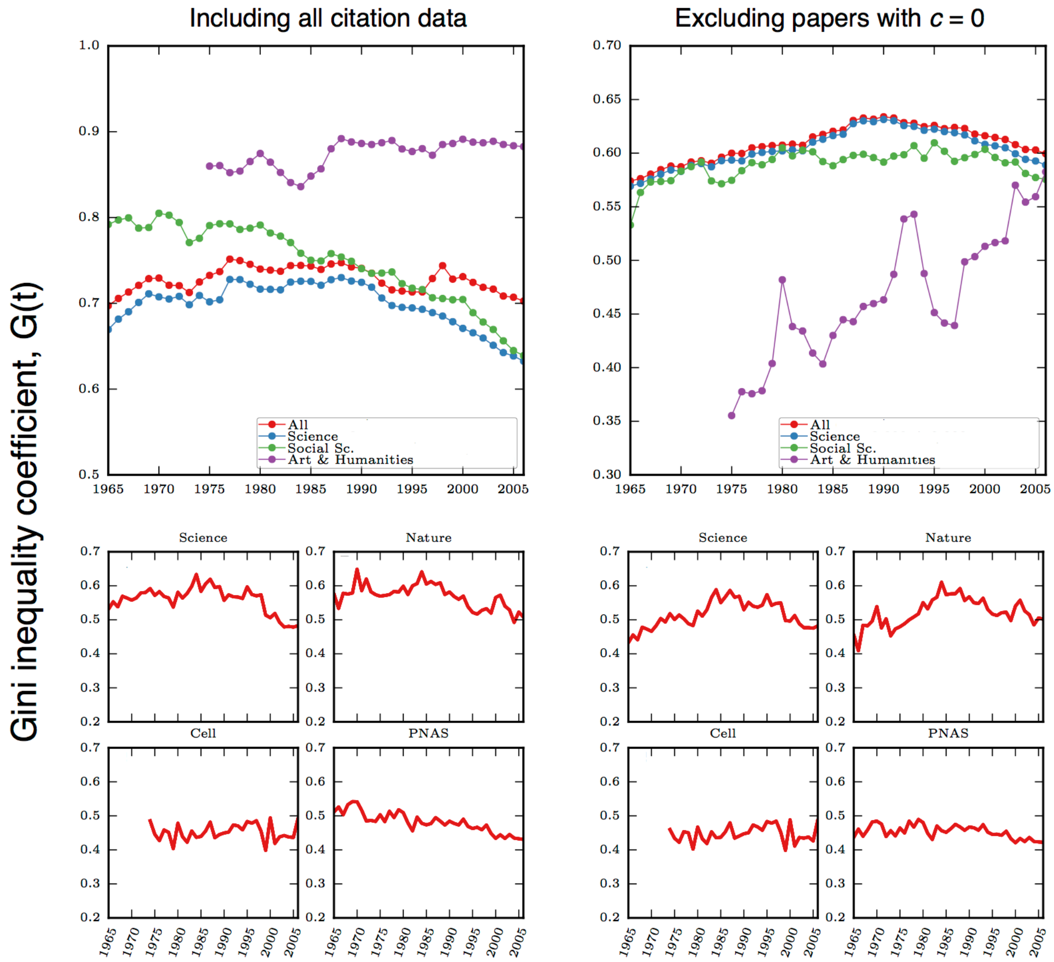


FIG. S4: **Empirical patterns of decreasing citation inequality.** The Gini inequality coefficient $G(t)$ is a standardized distribution measure which captures the relative concentration of citations with values ranging from 0 (all publications have the same number of citations) to 1 (extreme inequality, all publications have $c^p_{t,\Delta t=5} = 0$ except for one with $c^1_{t,\Delta t=5} > 0$). (top row) Gini index by subject area. (bottom row) Gini index by high impact journal. (left column) Gini coefficient calculated using all publications ($c^p_{t,\Delta t=5} \geq 0$). (right column) Gini coefficient calculated using only the publications with $c^p_{t,\Delta t=5} > 0$.

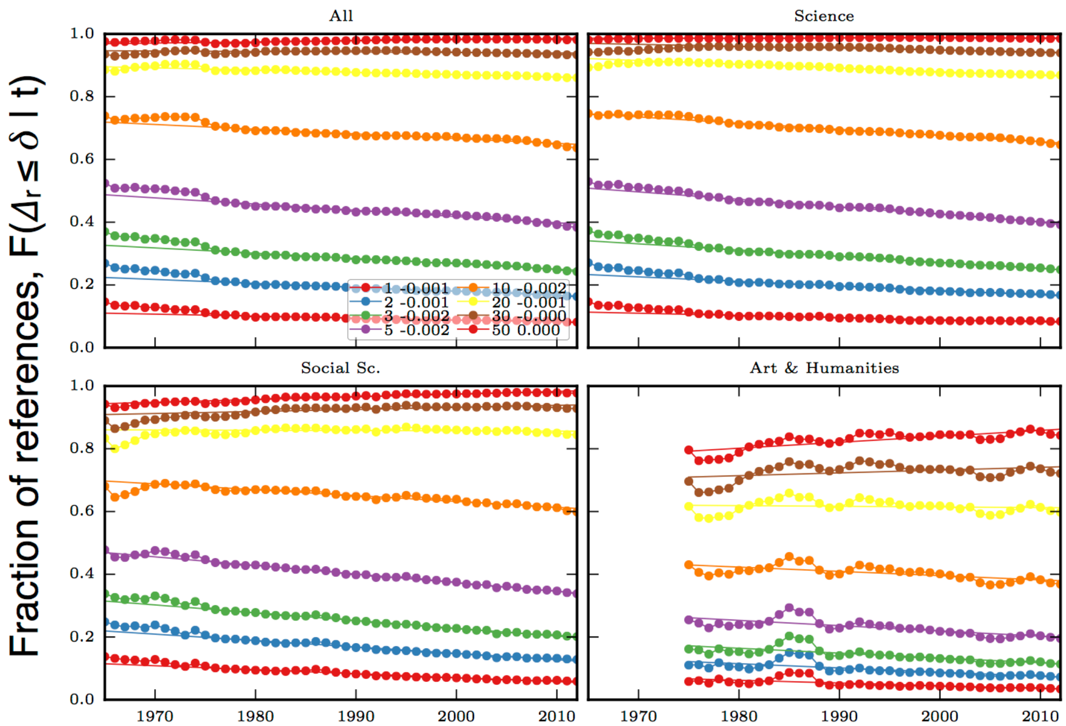


FIG. S5: **Empirical trends in reference distances.** The reference distance $\Delta_r = t - t_r$ is the number of years difference between the publication date $t$ of $p$ and the publication date $t_r$ of any reference $r$ appearing in its reference list. Shown is the fraction $F(\Delta_r \leq \delta|t)$ of references from year $t$ with $\Delta_r$ value falling within the time window $[t-\delta, t]$. The values of $\delta$ are 50 years (top curve), 30, 20, 10, 5, 3, 2, 1 year (bottom curve).

# Data description

Our data set consists of all publications (articles and reviews) written in English from 1965 till the end of 2012 included in the database of the Thomson Reuters (TR) Web of Science. For each publication we extracted its year of publication, the journal in which it is published and the corresponding references and citations to that publication. We used the TR journal classification to separate the publication data into 3 broad domains: (natural) “Science”, “Social Sciences”, and “Art & Humanities”. In total our analysis comprises of 32,611,052 publication and 837,596,576 references. We focus our analysis on the science and social science domains, which account for more than 95% of the data. Further, we concentrate our study on papers published after 1965, as it allows to include a sufficient number of papers for a statistically valid analysis. Note that there are many journals in TR that not classified in either Science, Social Science or Art & Humanities citation Index. The articles published in these journals are include in the category “All” along with those articles classified in Science, Social Sciences, Arts & Humanities index. As the unclassified journals are typically of low citation impact, when included in our analysis the results may differ slightly from other well classified journals.

Researcher profile data was obtained using TR “Distinct Author Sets” data as well as distinct researcher profile data from their subsidiary *ResearcherID.com*. For both the biology and physics subsets, we included 100 top-cited researchers [23, 56, 57, 60]. To complement these top-cited scientists with a sample of more typical researcher profiles, we collected biology and physics profiles from *ResearcherID.com* by querying the database for profiles listing any of the following keywords: “graphene”, “neuroscience”, “molecular biology”. For further details on the data selection see [57].

# Model description & benchmarking

## Network growth model

Our model is implemented in a strict network framework. That is, a fixed number of references are produced each year which are then allocated as links between the $n(t)$ incoming and the $\sum_{t'=0}^{t-1} n(t')$ existing nodes up to year $t$. This is unlike other citation "network growth" models in which stochastic differential equations are estimated and integrated for the "mean field" node, meaning that node-to-node correlations are not taken into account [41, 42, 45–47]. More importantly, we take the systemic route to simulating the citation network because it allows us to explicitly control $r(t)$ and $n(t)$, which is the starting point for determining the impact of the exponential growth of science on citation patterns. It also allows us to monitor the $\Delta_r$ produced by our model, as well as other dynamic features of the citation network which we are able to match to empirical benchmarks.

In particular, the model presented here is inspired by the Peterson et. al [45] citation network model, but with an enhanced triadic closure mechanism similar to [43]. The key development in our model is the fact that each new publication $i$ adds not only $j$ to its reference list, but also adds a random number of $x_{Binomial}$ indirect references – thereby contributing $x_{Binomial}$ triadic closures within the citation network. Thus, one crucial difference in our link-formation model is that the triadic closure rate is relatively high. This is measured by calculating the mean clustering coefficient $\overline{\psi}$: for the $N(T = 150) = 41,703$ nodes entering the network in the interval $t \in [1, 150]$ comprising $L(T = 150) = 379,454$ links, we calculate $\psi = 0.018$. This $\psi$ value is significantly larger than the baseline clustering coefficient value $q = 2N/(L^2 - L)$ expected of a random network. However, the $\overline{\psi}$ value produced by our model is significantly smaller than the values $\psi = 0.31$ (ArXiv) and $\psi = 0.17$ (PNAS) calculated for empirical citation networks [44]. This discrepancy is resolved when taking into consideration the discrepancy in the network sizes and the data used, as only partial snapshots of the citation network from highly correlated publication subsets are used in [44]. Thus, because our network is comprised of the entire system, the clustering coefficient is undoubtably expected to be considerably smaller, especially considering the limitations in the triadic closure due to small $r(t)$ for small $t$. Another novel feature of our model is the explicit exponential growth of the system, controlled by the parameters $g_n$ and $g_r$. And finally, by including $n(t)$ in the link dynamics governed by Eq. 2, we are able to reproduce non-monotonic attention life-cycles, even for the highly cited nodes (publications), which is not produced by pure $PA$ models in which the hubs grow uncontrollably. As a result, the node attachment rate (here representing citation rates $\Delta c^p(t)$) eventually decay exponentially in our model, as they typically also do in real systems.

We model the network growth using Monte Carle (MC) simulation based around the birth (publication) of $n(t)$ nodes (publications) in time step $t \geq 0$. The scientific publication base starts from a tiny seed at $t = 0$ with $n(t = 0) \equiv 10$ disconnected nodes. The number of new publications in each Monte Carlo period $t$ is $n(t) = n(t = 0) \exp[g_n t]$, where $g_n \equiv 0.033$ is the node (publication) growth rate, using the approximate empirical values reported here for the Science. Similarly, the number of outgoing links (references) $r(t)$ per node (publication) also grows exponentially, $r(t) = r(0) \exp[g_r t]$, using the empirical growth rate value $g_r \equiv 0.018$ and initial reference list length $r(0) \equiv 1$ references. Using these growth parameters, we sequentially add cohorts of $n(t)$ nodes to the network over $t = 1...T$ periods according to the following prescription:

**Network growth rules:**

1. **System Growth:** In each period $t$, we introduce $n(t)$ new publications (nodes), each with a reference list of length $r(t)$. As such, the total number of references produced in $t$ is $R(t) = n(t)r(t)$. Also, since the seed publications from period $t = 0$ are foundational, they have reference lists of length 0.

2. **Link Dynamics:** For each new publication $i \in n(t)$:

   **(a) Direct citation** $i \to j$**:** Each new publication $i$ starts by referencing 1 publication $j$ from period $t_j \leq t_i$ (where $t_i = t$ by definition). The publication $j$ is selected proportional to the weight $\mathcal{P}_{j,t} \equiv (c_\times + c_t^j)[n(t_j)]^\alpha$ given by Eq. (2). The factor $c_t^j$ is the total number of citations received by $j$, tallied at the end of period $t - 1$, representing a linear preferential attachment link dynamics [45, 48–51]. The factor $n(t_j)$ is the number of new nodes introduced in cohort $t_j$ of $j$, and represents the endogenous crowding out of old literature by new literature. The parameter $c_\times$ is a citation offset controlling for the citation threshold, above which preferential attachment "turns on" [23, 41, 46]. It is needed so that a sufficient number of references go to publications with $\Delta_r \lesssim 5$ in the citation distribution. In this way, the preferential attachment mechanism is less sensitive to $p$ with for $c^p < c_\times$. The parameter $\alpha$ controls the rapidity of the obsolescence, as indicated by the ratio of the attachment rates between any two given publications with $t_{j'} \geq t_j$,

$$\mathcal{P}_{j,t}/\mathcal{P}_{j',t'} = \Big(\frac{c_\times + c_t^j}{c_\times + c_t^{j'}}\Big) \exp[-\alpha g_n(t'-t)] \ . \tag{S1}$$

**(b) Redirection** $i \to s(j)$**:** The referencing publication $i$ then cites a random number $x$ of the publications contained in the references list $\{s\}_j$ (of length $S_j$) of publication $j$. The probability of selecting $x$ references is given by the binomial distribution

$$P(x=k) = \binom{S_j}{k} (q)^k (1-q)^{S_j-k} \ , \tag{S2}$$

with success rate $q = \lambda/S_j$ and average value $\langle x \rangle = \lambda$. Thus, we select a random number $x_{Binomial(S_j,\lambda/S_j)}$ according to a prescribed rate of redirected citations per direct citation,

$$\lambda = r^{(2)}/r^{(1)} = \beta/(1-\beta) \ , \tag{S3}$$

where $0 \leq \beta \leq 1$ is the prescribed fraction of total references $r(t)$ that are made according to step $(b)$. In this way, on average, the total number of redirected references is $r^b(t) = \beta r(t)$ for any $t$. Once the sample size $x$ is determined, the $s(j)$ are selected from the reference list proportional to the same weights used in step (a), $p_{s(j),t} = (c_\times + c_{s(j),t})[n(t_{s(j)})]^\alpha$, which again gives preference within this secondary redirection process to the references with larger $t_{s(j)}$. We do not allow $i$ to add any given $s(j)$ more than once to its reference list. Note that the quantity $q = \lambda/S_j$ represents the Bernoulli trial success rate, which for small $t$ can be greater than unity if $\lambda > S_j$; thus, for small $t$ we use $q = Min(1, \lambda/S_j)$. For large $t$, encountering this scenario is not very likely, as most candidate $j$ selected for large $t$ have $S_j > \lambda$. In other words, this subtle modeling limitation is only important in the beginning of the simulation when $r(t) < \lambda$, and plays an insignificant role on the system evolution thereafter.

**(c) Stop according to fixed reference list length:** The referencing process alternates between (a) and (b) until publication $i$ has referenced $r(t)$ publications.

3. Repeat 2 for each new publication in period $t$. At the end of each $t$ the weights $\mathcal{P}_{j,t}$ are updated.

4. Perform steps (1-3) for $t = 1...T$.

# Model benchmarking and case studies of parametric perturbations

**Testing the model against empirical benchmarks.** The base parameter set we used are: $T \equiv 200$ MC periods (years), $n(0)$ = 10 initial publications, $r(0) \equiv 1$ initial references, exponential growth rates $g_n \equiv 0.033$ and $g_r \equiv 0.018$, secondary redirection parameter $\beta \equiv 1/5$ (corresponding to $\lambda = 1/4$), citation offset $c_\times = 6$, and life-cycle decay factor $\alpha \equiv 5$. Each model realization was simulated to size $N(T) = 218,698$ nodes at the time of the stopping time $T = 200$, with final reference list length $r(T) = 35$. We manually explored the parameter space of ($\alpha$,$\beta$, $c_\times$) to determine the combination which best reproduces various empirical regularities known for the structure of citation network and the dynamical citation patterns of individual publications.

We summarize a typical network produced by our model in the three figures S6-8. First, Fig. S6(A) shows the exponential growth of $n(t)$, $r(t)$, and $R(t)$ as determined by the empirical parameters $g_n$, $g_r$, and $g_R$. In Figs. S6(C-I) we visualize various quantities measured from the synthetic citation network, such as: the mean reference distance $\langle \Delta_r \rangle$, the fraction of uncited publications $F(c \leq C|t)$, the mean citation lifecycle $\langle \Delta c(\tau|t)$ calculated across the $p$ for the $\tau$ periods after the publication year $t$, the mean $\ln \mu$ and standard deviation $\sigma_{LN}$ of the natural log of the number of citations received by $p$ from each $t$, the log-normal distribution of the normalized citations $z_t$, the evolution of the citation share of the top and bottom percentile groups $F_{\sum c}(Q|\tau, t)$, and some typical citation trajectories $c_t^p$ produced by the model. Second, Fig. S7 shows the results of a simulation without redirection ($\beta = 0$) while varying $g_n$ and $g_r$ And finally, Fig. 8 shows the model results while varying $\beta$ and varying $g_r$.

Figure S5 shows the fraction $F(\Delta_r \leq \delta|t)$ of references from year $t$ falling within the time window $[t-\delta, t]$ years. The model also reproduces the decreasing $F(\Delta_r \leq \delta|t)$ for $\delta \leq 20$, with the fastest decay for $\delta = 5$, pointing to the fact that relatively new literature is being cited less and less, as a percentage, over time. This is also evident in the $P(\Delta_r|t)$ and $CDF(\Delta_r|t)$ panels shown in Figs. S7 and 8.

The log-normal distribution citations – within cohort – is another statistical benchmark that our model reproduces. To show this, we took all the publications with $c_t^p > 0$ from a given cohort $t$ and calculated the average $\mu_{LN,t} = \langle \log(c_t^p) \rangle$ and the standard deviation $\sigma_{LN,t} = \sigma[\log(c_t^p)]$ of the log citation count. Fig. S6(E) shows the evolution of $\mu_{LN,t}$ and $\sigma_{LN,t}$. The normalized citation counts $z_t^p$ are appropriately scaled by these cohort-dependent location and scale parameters. Fig. S6(E) shows the probability distribution $P(z_t)$ for varying cohorts (grouped over 20-year intervals). Each $P(z_t)$ distribution collapses onto the universal log-normal curve $N(0,1)$ with mean $\mu_{LN} = 0$ and standard deviation $\sigma_{LN} = 1$, except for in the lower tail where the log transform of small citation counts does not behave well. This log-normal distribution is a fundamental benchmark, representing a universal pattern observed for the within-cohort normalized citation distribution [54].

We also show in S6(G) that the model reproduces the increasing dominance of the top 1% of publications from each cohort $t$, consistent with empirical findings within high-impact journals [18]. To demonstrate this, we calculated $F_{\sum C}(1\%|t,\tau)$ which is the fraction of the total citations $\sum_p c_t^p$ accrued by the top 1% of publications from cohort $t$ in year $\tau$ ( the top1% is determined by ranking the $p$ according to $c_t^p$ after $\tau = 20$ periods), where $\tau$ is the number of years since publication. Fig. S6(H) shows how the complementary bottom 75% of publications loses its citation share over time, largely because the lower-cited publications have a shorter citation lifecycle. Figure S6(I) shows a sample of the top-200 cited $p$ (ranked at t=180) from the cohorts $t \in [170-180]$, demonstrating growth and mixing of citation trajectories, consistent with real citation curves [23].

**The role of the key parameters.** The size of each new cohort $n(t)$ plays a key role in mediating the intrinsic citation lifecycle induced by crowding out of old nodes by new node, as mediated by the parameter $\alpha$ (see Eq. [1]). This follows from the quantity $1/(\alpha g_R) \approx 4$ periods, which determines the natural decay time scale of a publications citation attractiveness and governs the balance between preferential attachment effect and the crowding-out effect. The parameter $\alpha$ cannot be too large or too small. If $\alpha$ is too small, then preferential attachment dominates and the share of references to recent publications is significantly smaller than what we observe empirically because there is no crowding-out effect. Contrariwise, if $\alpha$ is too large, then the citation lifecycle decays too quickly meaning too large of a concentration of references on recent literature, which also eliminates the increasing dominance of the top 1% because their citation rates also decay to zero for large $\tau$. In this way, a smaller $\alpha$ can be seen as increasing the citation equality.

We used the value $\alpha \equiv 5$ which produces a peak citation timescale that is consistent with he empirical peak citation time scale of a few years found by Parolo et al. [5]. Furthermore, for $\tau \gg \tau_{peak}$ the mean citation rate $\langle \Delta c(\tau|t) \rangle$ of the typical $p$ from $t$ decays exponentially as demonstrated by the approximately linear decay when plotted on log-linear axes, see Fig. S6(D). The peak citation year also appears to decrease and the exponential decay rate appears to increase for larger $t$, signaling that obsolescence is increasing due to systemic crowding out.

The citation offset $c_\times$ is also important for shifting the peak in $P(\Delta_r|t)$ to smaller values, around $\Delta_r = 2$ to 3 periods. This occurs because $c_\times$ draws more citations to newer publications since it effectively diminishes the role of preferential attachment for the newer nodes with $c < c_\times$. We found that the fraction $F(c \leq C|t)$ of nodes with less than $C$ citations decreases faster with $t$ with larger $c_\times$ values. For the value $c_\times \equiv 6$ we observed a rapidly decaying uncited fraction, $F(c \leq 0|t)$ which is notably faster than the empirical curves shown in Figs. 4 and S3. This discrepancy likely arises from the fact that our model does not incorporate intrinsic variation in publication "quality" (i.e. fitness [47]), which is analogous to all the $p$ being drawn from a single journal with the same impact factor. In other words, the empirical $F(c \leq C|t)$ do not decay as quickly as the model, most likely because of impact factor heterogeneity – there are many more journals with low impact factor than with relatively large impact factor in the aggregate TR dataset.

The parameter $\beta$ controls the rate at which references are made according to the redirection process (b) relative to the random (with $PA$) referencing process (a) (see Fig. 6). These two processes correspond to the two modes of "searching" described by Evans [19], the first being a "browsing" mode, the second being a "redirection" mode that is facilitated by online journals and indexes that have 1-click "hyperlinks". Thus, our model allows us to mechanistically test Evans' theory about the impact of electronic media on citation "inequality" and narrowing scholarship, i.e. "myopia" in science. Since redirected citations on average go to older papers, this parameter can be used to tune the mean reference distance $\langle \Delta_r|t \rangle$, which in our model grows linearly in time, from roughly 6 periods in $t = 60$ to 10 in $T$, see Fig. S6(B). This feature is also verified by noting that increasing $\beta$ also shifts the distribution $P(\Delta_r)$ towards larger $\Delta_r$ values in the bulk of the distribution.

**Simulation without the redirection parameter:** $\beta = 0$**.** Figure S7 shows the results of the simulation when we excluded the redirection mechanism $(b)$ by setting $\beta = 0$. Comparing the benchmarks in the first column of Fig. S7 for $\beta = 0$ with the first two columns of Fig. 8 for $\beta = 1/5$ and $\beta = 2/5$, respectively, the citation inflation quantified by $C(q|t)$, the citation inequality quantified by $G(t)$, and the distribution of reference distances quantified by $F(\Delta_r \leq \delta|t)$, $P(\Delta_r|t)$ and $CDF(\geq \Delta_r|t)$ are qualitatively similar. There are, however, differences in the decay of $G(t)$, which is faster for the case $\beta = 0$ and the decay of $F(\Delta_r \leq \delta|t)$, which is faster for larger $\beta$, mainly because the redirection mechanism facilitates the citation of older publications. Also, the bulk of the distribution $P(\Delta_r|t)$ is wider as $\beta$ increases, representing the redirection of references into the range $[\Delta_r^-, \Delta_r^+] \approx [8, 45]$.

We also performed three sudden parametric perturbations to gain a better understanding of how the inflation of science, attention inequality, and the obsolescence of knowledge are related:

**The role of system growth: quenching the system growth, perturbations of $g_n$ and $g_r \to 0$.** The second column of Fig. S7 shows the results of perturbing the system at $t = 165$ by suddenly quenching the system growth: $g_n \to 0$ and $g_r \to 0$ for $t \geq 165$. These two perturbations mean that a constant $n(t \geq 165) = 2168$ number of new nodes (publications) are added each period (year) thereafter, with each publication having a constant reference list length $r(t \geq 165) = 18$. This simulation demonstrates how the growth of the system sustains the citation of recent publications, because after $t = 165$ the citation values $C(q|t)$ suddenly drop as most of the references are drawn to the highly cited publications because the crowding out effect is not as strong as when there is sustained growth.

**Increasing the rate of "hyperlinking" by perturbing the redirection parameter $\beta$.** The third column Fig. 8 shows the result of suddenly increasing the rate of redirection from $\beta = 1/5$ to $\beta = 2/5$ at $t = 165$. This perturbation causes a decrease in $C(q|t)$ and an increase in $G(t)$ because more references are redirected to older publications as demonstrated by the shifts in $F(c \leq C|t)$, $P(\Delta_r|t)$ and $CDF(\geq \Delta_r|t)$ towards $\Delta_r$ in the intermediate range $[\Delta_r^-, \Delta_r^+] \approx [8, 45]$.

**Increasing the length of reference lists: perturbation of the growth rate parameter $g_r$.** The third column of Fig. S7 (with $\beta$=0) and the fourth column of Fig. 8 (with $\beta$=1/5) show the result of increasing the reference supply by suddenly increasing $g_r$ from 0.013 to 0.019 at $t = 165$. This perturbation causes a significant increase in $C(q|t)$ and a decrease in $G(t)$ as the increasing supply of references is distributed to a larger share of the publications, demonstrating the relation between growth and decreasing inequality. Nevertheless, as in the perturbation of $\beta$, the increasing supply of references going through the redirection process (b) means that more references are redistributed to the intermediate range $[\Delta_r^-, \Delta_r^+] \approx [8, 45]$ of $P(\Delta_r|t)$.

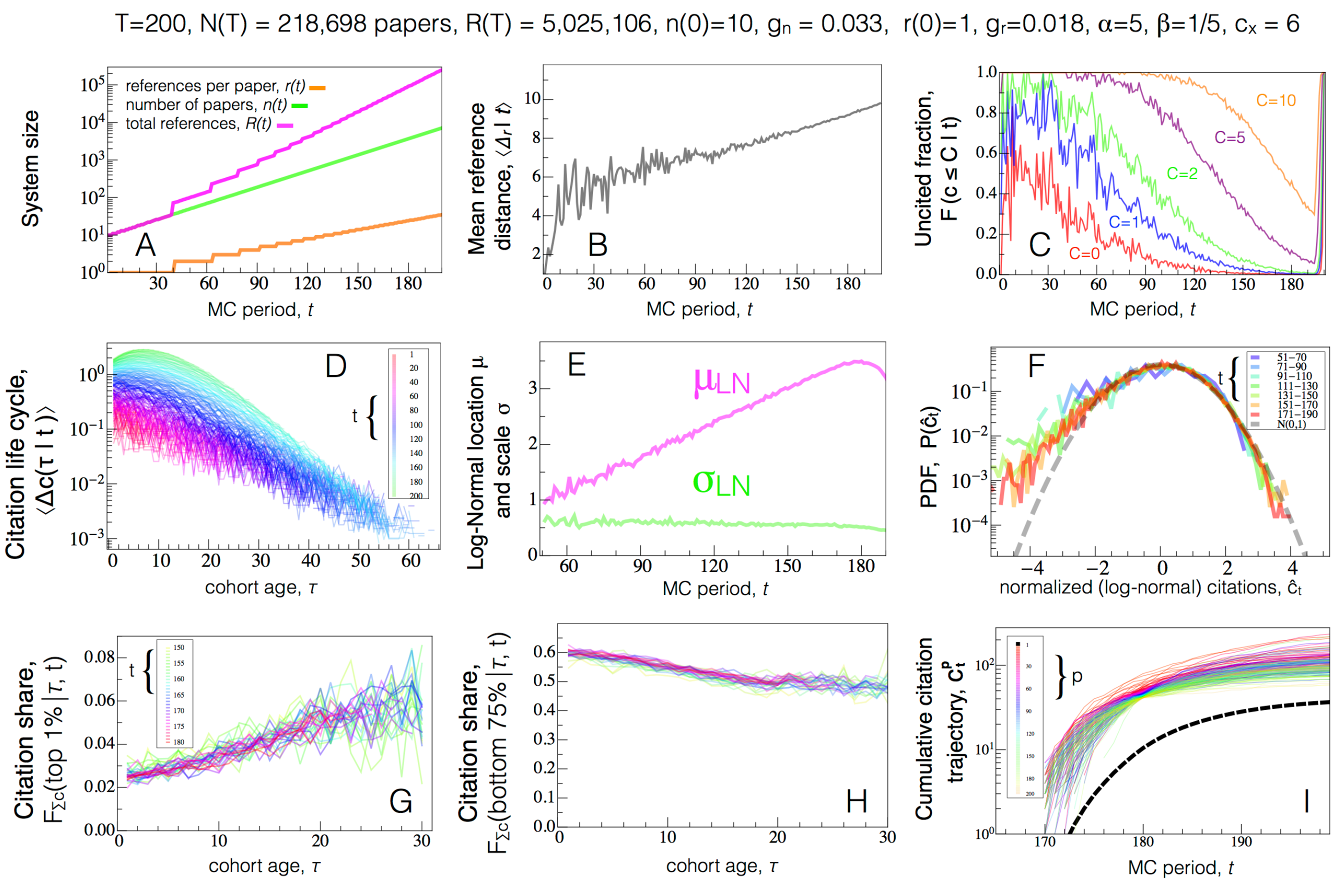


FIG. S6: **Monte-Carlo growth parameters and benchmark validation.** Shown are various properties of the synthetic citation network that can be compared with empirical trends. We evolved the simulation using the parameters: $T \equiv 200$ MC periods ($\sim$ years), $n(0) \equiv 10$ initial publications, $r(0) \equiv 1$ initial references, exponential growth rates $g_n \equiv 0.033$ and $g_r \equiv 0.018$, secondary redirection parameter $\beta \equiv 1/5$ (corresponding to $\lambda = 1/4$), citation offset $C_\times \equiv 6$, and life-cycle decay factor $\alpha \equiv 5$. At the final period $t = T$, the final cohort has size $n(T) = 7112$ new publications, $r(T) = 35$ references per publication, and final citation network size $N(200)$ = 218,698 publications (nodes) and $R(T)$ = 5,025,106 total references/citations (links). (A) The size of the system in each MC period $t$. (B) Growth of the mean reference distance $\langle \Delta_r \rangle$. (C) The fraction $f_{c \leq C}(t|\tau = 5)$ of publications which have $C$ or less citations at cohort age $\tau = 5$. (D) The citation life cycle, measured here by the mean number of new citations $\tau$ periods after entry (publication). The different curves correspond to the publication cohort entry period $t$. For sufficiently large $t$ the life cycle decays exponentially. (E) Growth of the log-normal mean (location) value $\mu_{LN,t}$ and the relative stability of the log-normal standard deviation (scale) value $\sigma_{LN,t}$. $\mu_{LN,t} = \langle \log(c_t^p) \rangle$ and $\sigma_{LN,t} = \sigma[\log(c_t^p)]$ are the log-normal mean and standard deviation calculated across all $p$ within each age cohort $t$. (F) The probability density function $P(z_t^p)$ for the normalized citation value $z_t^p \equiv (\log(c_t^p) - \mu_{LN,t})/\sigma_{LN,t}$. For visual comparison we plot the Log-Normal distribution $N(\mu = 0, \sigma = 1)$. (G) The increasing citation share $f_{\sum c}$ – the fraction of the total citations received by all publications from cohort $t$ – of the top 1% of publications from cohort $t$ (ranked at cohort age $\tau = 10$). (H) The decreasing citation share $f_{\sum c}$ of the bottom 75% of publications. (I) The cumulative citation count $c^p(t)$ of the top 200 publications ($p$) from the interval $t = [170, 179]$, ranked according to $c^p(t = 180)$. The dashed line represents the average citations for $p$ from the same cohort over the same period.

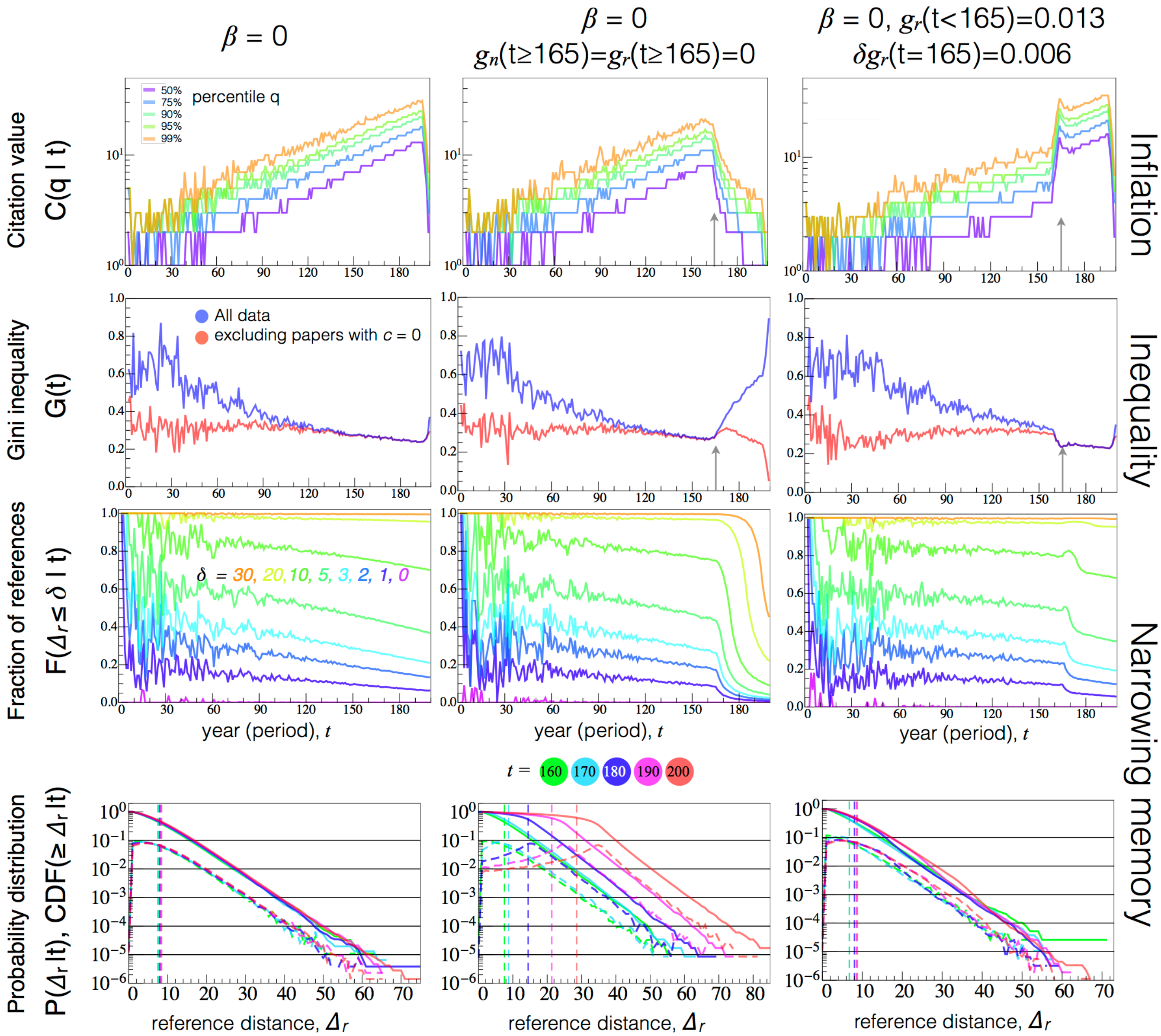


FIG. S7: **Monte-Carlo simulation of the science citation network: without the redirection mechanism** ($\beta = 0$). We benchmark the model using empirical trends observed in the real citation data. For each simulation, we use $\beta = 0$ meaning that there is no redirection mechanism. The only difference between the columns is in the growth of the system: in column 2 the growth rate of the system is quenched at $t = 165$ so that $n(t \geq 165) = n(164)$ since $g_n(t \geq 165) = 0$ and $r(t \geq 165) = r(164)$ since $g_r(t \geq 165) = 0$; in column 3 the growth rate of the reference lists is boosted at $t = 165$ so that $g_r(t < 165) = 0.013$ and $g_r(t \geq 165) = 0.019$. (First row) Inflation demonstrated by the persistent exponential growth of the citation value $C(q|t)$ corresponding to the quantile $q$ indicated in the plot legend. For example, the citation value corresponding to the 99th percentile grows from roughly 10 in $t = 90$ to 30 in $t = 190$ for the unperturbed simulation. (Second row) The Gini index $G(t)$ of the total number of citations after 5 years from publication measures the citation inequality of the citation distribution. (Third row) The fraction $F(\Delta_r \leq \delta|t)$ of citations from year $t$ going to publications within the interval $[t - \Delta_r, t]$ are all decreasing; the sharp decline for the perturbed growth scenario shows the importance of growth on sustaining attention to the recent literature base. (Fourth row) The cumulative distribution $CDF(\geq \Delta_r|t)$ (solid lines) and the probability density function $P(\Delta_r|t)$ (dashed lines) of reference distance $\Delta_r$, conditional on the publication cohort $t$. Vertical lines indicate the mean of each conditional distribution for varying $t$. To improve the data size, each $P(\Delta_r|t)$ and $CDF(\geq \Delta_r|t)$ are calculated by pooling the reference data from the 3-period interval $[t - 2, t]$.