Appendix A
Details of Numerical Simulation

In our numerical simulations of citation dynamics of 40,195 Physics papers published in 1984 we used the following parameters. $\gamma + \beta = 1.2$ yr^{-1}, as found in our measurements of indirect references and citations; $m_{dir}(t)$ from Fig. 10 (see main text). We assumed that $n^{nn}(t)$ dependence mimics $m(t)$ dependence, namely $n^{nn}(t) = \frac{m(t)}{\bar{s}}$ where $\bar{s} = 1.2$ is the average over all Physics papers published in 1984 and $M(t)$ is shown in Fig. 6 (main text). With respect to $\tilde{P}_0(K)$, it is given by the following expression: $\tilde{P}_0(K) = Pf(K)$ where $P = 0.34$ and $f(K) = 1 + 0.82 \log K$. Here, $P = 0.34$ characterizes the probability of indirect citations for low-cited papers, and $f(K)$ stays for logarithmic correction which is most important for highly-cited papers.

We can assemble all time-dependent functions in the kernel together, in such a way that Eq. 4.9 reduces to

$$\lambda_i(t) = \eta_i m_{dir}(t) + \sum_{\tau=1}^{t} f(K_i)F(t-\tau)k_i(\tau) \tag{A.1}$$

where $F(t) = Pn^{nn}(t)e^{-(\gamma+\beta)t}$. For the Physics papers published in 1984 we find $F(1) = 0.089$, $F(2) = 0.138$, $F(3) = 0.046$, $F(4) = 0.012$, $F(5) = 0.0035...$ Thus, at first F grows with time as the paper receives more recognition (there is approximately one year delay between the publication of the paper and its first citation) and then decays exponentially. This obsolescence is strong, hence the memory of the citation process is restricted to a few years.

In our numerical simulations we used Eq. A.1. For approximate calculations one can also use a simplified numerical scheme according to which Eq. A.1 is considered as an autoregressive model. We looked for the model of minimum order

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that can faithfully represent our measurements and found that the first-order model is unsatisfactory while the second-order autoregressive model

$$\lambda_i(t) = \eta_i m_{dir}(t) + [1 + 0.82 \log K_i(t)][0.09k_i(t) + 0.19k_i(t-1)] \tag{A.2}$$

is more satisfactory. This means that to approximately predict the number of citations that a paper garners in the year $t + 1$ after publication, in most cases it is enough to know its citation history during previous couple of years: t and $t - 1$. Thus our results validate the widespread use of the 2-year impact factor.

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M. Golosovsky, *Citation Analysis and Dynamics of Citation Networks*,
SpringerBriefs in Complexity, https://doi.org/10.1007/978-3-030-28169-4